

AIN311

Fundamentals of Machine Learning

Lecture 1:
Course outline and logistics,
An overview of Machine Learning

Today's Schedule

- Course outline and logistics
- An overview of Machine Learning

Course outline and logistics

Logistics

- **Instructor:**



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- **Teaching Assistant:**



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- **Lectures:** Mon 11:40 - 12:30 @D4
Wed 09:40 - 11:30 @D1
- **Tutorials:** Fri 09:40 - 11:30 @D10

About this course

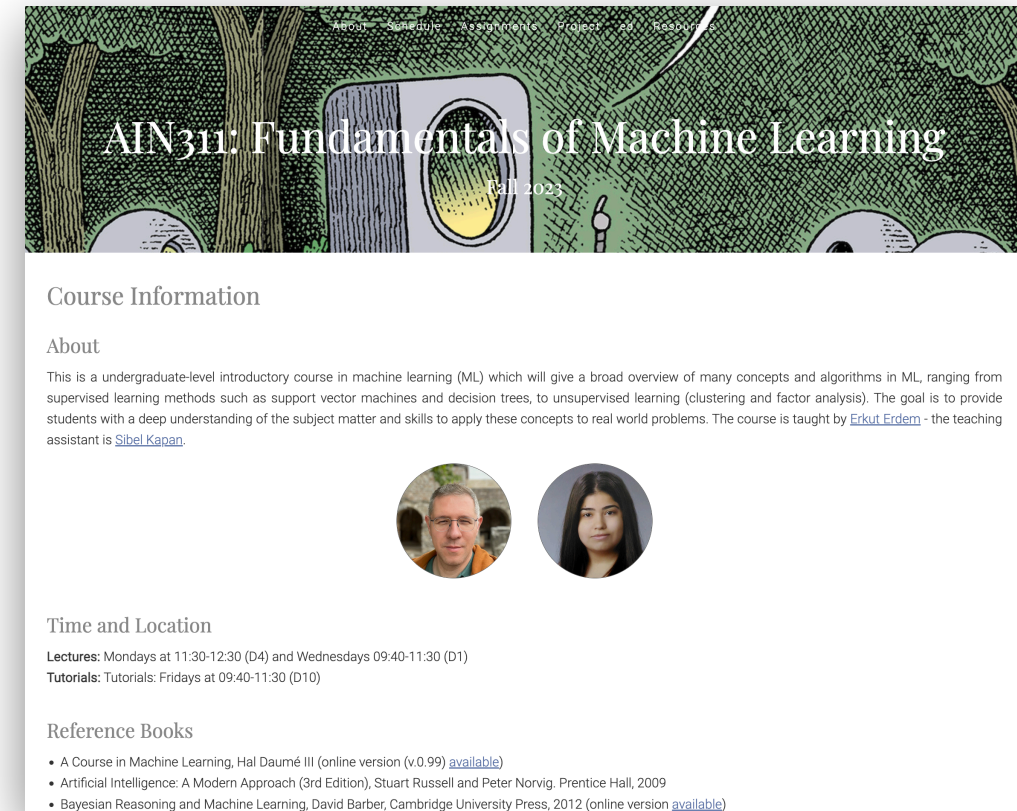
- This is a undergraduate-level introductory course in machine learning (ML)
 - A broad overview of many concepts and algorithms in ML.
- **Requirements**
 - Basic algorithms, data structures.
 - Basic probability and statistics. common distributions, Bayes rule, mean/median/mode
 - Basic linear algebra and calculus vector/matrix manipulations, partial derivatives
 - Good programming skills
- **AIN 313 Machine Learning Laboratory**
 - Students will gain skills to apply the concepts to real world problems.

Communication

- **Course webpage:**

<https://web.cs.hacettepe.edu.tr/~erkut/ain311.f23/>

- The course webpage will be updated regularly throughout the semester with lecture notes, programming and reading assignments and important deadlines.

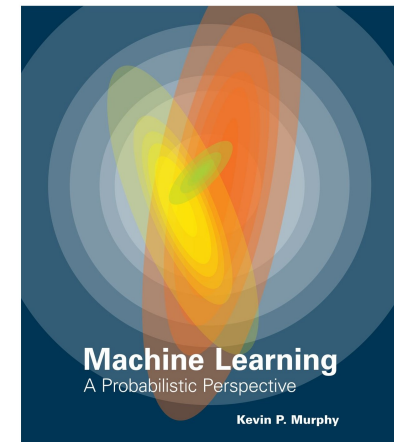
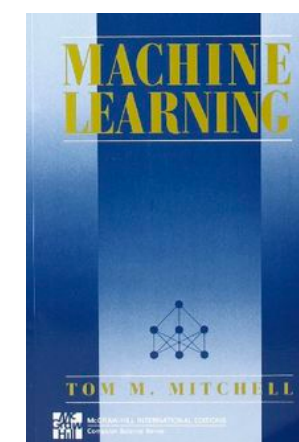
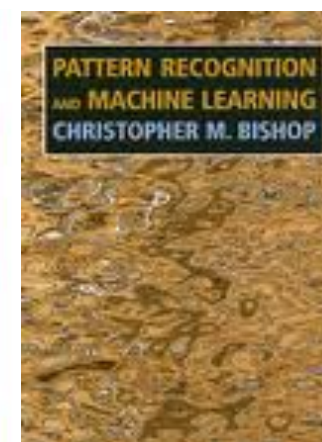
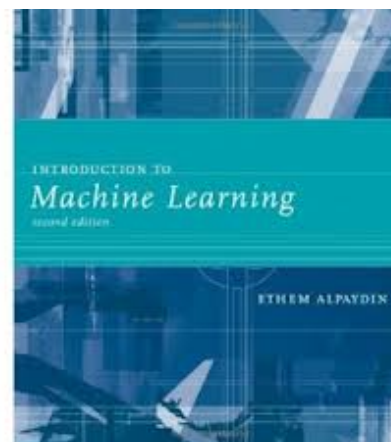
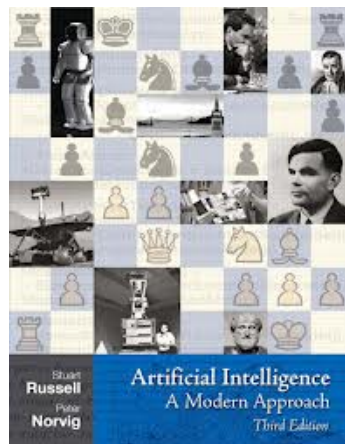
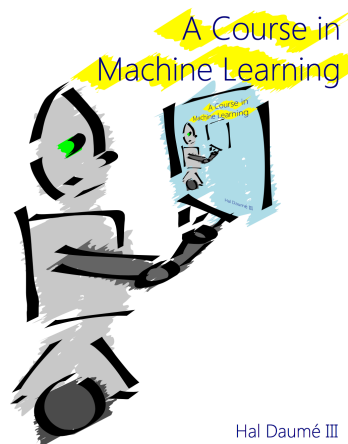


- We will be using eds for course related discussions and announcements. Please enroll the class on ed by following the link

<https://edstem.org/eu/join/KXqbx8>

Reference Books

- A Course in Machine Learning, Hal Daumé III, 2017 (**available online**)
- Artificial Intelligence: A Modern Approach (3rd Edition), Russell and Norvig. Prentice Hall, 2009
- Bayesian Reasoning and Machine Learning, Barber, Cambridge University Press, 2012 (**available online**)
- Introduction to Machine Learning (2nd Edition), Alpaydin, MIT Press, 2010
- Pattern Recognition and Machine Learning, Christopher Bishop, Springer, 2006 (**available online**)
- Machine Learning, Tom Mitchell, McGraw Hill, 1997 (**available online**)
- Machine Learning: A Probabilistic Perspective, Murphy, MIT Press, 2012



Grading Policy

- Grading for AIN 311 will be based on
 - course project (**done in groups of 2 students**) (35%),
 - midterm exam (30%), and
 - final exam (35%)
- In AIN 313, the grading will be based on
 - a set of quizzes (20%) (**the lowest quiz grade will be dropped**), and
 - 3 assignments (80%) (**done individually**)

Assignments

- 3 assignments
 - First one worths 20%, last two worth 30% each
- **Theoretical:** Pencil-and-paper derivations
- **Programming:** Implementing Python code to solve a given real-world problem
- A quick Python tutorial in this week's tutorial session.



**KEEP
CALM
AND
DO YOUR
HOMEWORKS**

Course Project

- Done in groups of 2 students.
- Choose your own topic (but focused on a specific theme) and explore ways to solve the problem
- This year's theme is will be announced soon.
- **Proposal:** 1 page (Nov 6) (2%)
- **Project Blogs:** Regular blog posts (4%)
- **GitHub commits and meetings with TA:** (5%)
- **Progress Report:** 3-4 pages (Dec 18) (6%)
- **Project Presentation:** Classroom presentation and video presentation (Jan 3) (8%)
- **Final Report:** 6-8 pages (Jan 7) (10%)

Sample projects from 2016 (BBM406)

BBM 406 Class Project - Final Report

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Abstract

This paper is a final report of our project "What Am I Eating?" for BBM406 Introduction to Machine Learning lesson. "What Am I Eating?" is an image recognition project which predicts food labels from given images. Developments in the field of Machine Learning and increase of datasets in recent years encourage us to make an image recognition project. We are using deep learning. We performed transfer learning (from Inception v3 model [Szegedy et al. 2015]) and data augmentation. Our dataset is a combination of different datasets which has 113 classes. Each class has 1000 images.

Keywords: deep learning, image recognition, fine tuning

1 Introduction

In recent years there have been major developments in the field of machine learning. The datasets have grown up because of the increase in internet usage. Hardwares become stronger than before. Graphic cards become cheaper. Because of these conditions, researches have increased and new approaches such as deep learning has appeared. Open source libraries were developed.

Deep Learning is a new and very popular area of Machine Learning research. We decided to develop a project using deep learning to improve ourselves in this field. Deep learning is used in many areas such as image recognition, speech recognition, natural language processing and so on. We used deep learning for image recognition. So, What am I Eating? is a deep learning project that recognizes foods from images.

We saw that no dataset has any Turkish foods. We wanted our project to recognize Turkish foods too. Also we have some future thoughts about our project.




Figure 1: pizza (score = 0.84349), waffle (score = 0.04952), bruschetta (score = 0.02402), omelette (score = 0.01936), ...

2 Related Work

There are three researches which are closely related to our research topic. All of them are new and made in 2016. One of them is [Liu et al. 2016]. The purpose of this research is to improve the accuracy of current measurements of dietary intake by analyzing the food images captured by mobile

PREDICTING RESTAURANT RATINGS FROM REVIEW TEXTS

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ABSTRACT

Nowadays, with the growth of crowd-sourced review website, the quality of business is determined by its ratings and reviews. The customer and the business owner will be able to see the trends, making decision, and getting recommendations based on their preferences just by looking at the reviews and ratings themselves. In this project, our goal is to predict the ratings which is given to a restaurant by looking at its review text. We use Yelp Dataset for our training and testing. By applying machine learning and text mining principle, we analyzed the review text from the Yelp Dataset. We were researching for the best algorithm which would give us the best result. The algorithms which we used at this projects are Bayesian Ridge Regression, Support Vector Regression, and Random Forest Regression.

1 INTRODUCTION

The development of technology makes it easier for people to make the right decisions. In this matter, technology influences the field of business by delivering a more convenient way for people to evaluate their business. For example, nowadays customer may look at the reviews and ratings which has been given and getting influenced by it, before deciding to go to a certain restaurant.

The goal of our project is to choose a supervised machine learning algorithm which will give us the best performance in predicting the restaurant ratings by looking at its review text that has been given in Yelp Dataset. Firstly we have to choose the most appropriate dataset to our problem. After that, in order to work with Machine Learning algorithm, we transform our raw data into vector or matrices form.

For our project we use Yelp Dataset, since it already provides the review and rating in an easily accessible format. Then, we did feature extraction from our dataset. We combined several feature extracting process in order to get the better result. For this, we use Bag of Words and Word2Vec model. We have tested these model and it gave us a satisfying result. For the better result, we also removed words which we considered unimportant. After we made our model, we use machine learning algorithm to test our model. We then choose the algorithm which gave us the best performance after we tested it. We treated this problem as regression problem, therefore we used regression algorithm. We made use of Yelp Dataset as our training set and testing set.

In this report, firstly, we will present you the dataset. Secondly, we will tell you about our feature extraction method (Bag of Words, Word2Vec). The next part is that we will explain about the algorithm which we use for this projects, which consists of Bayesian Ridge Regression, Support Vector Regression and Random Forest Regression. Then, by using Explained Variance Score (R^2 score) and Mean Square Error we calculate the accuracy of our model. We will share the result and the conclusion of our project by the last part of this report.

Finding The Ingredients of Pizza Using Deep Learning

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Abstract

Extracting ingredients from a dish can be a powerful tool for combatting obesity and making food inspection processes easier. For this purpose, we tried to create a program which extracts ingredients from a pizza, using convolutional neural networks. We also created a dataset which has 7405 images and 20 different labels as ingredients. Our experiments show us our model can predict small numbers of ingredients successfully (80 percent for one label), however as the number of ingredients increased, accuracy rate drops significantly (22 percent for 2 labels).

1. Introduction

Our aim is to create a model which can identify ingredients in the pizza. Our program should output a list of ingredients as output when feed with an image of a pizza.

First of all, we started with creating a new dataset from the scratch, because we couldn't find any ready-to-use dataset. To do this, we collected about twenty five thousand images from web and labeled all of them by hand with a little software we created for this purpose.

Secondly, we decided to use a Convolutional Neural Network, because they show much better performance in image recognition problems compared to other approaches. Also when using Convolutional Neural Networks, we don't need to extract any features because CNN's operates directly on images. There is also some downsides of using Convolutional Neural Networks as they need more data and require more computing power than other solutions.

Finally, we evaluated our project with the result that we get after the process of training our classifier model which we present in the results section.

Hardest part of this problem is, because food shapes are deformed after cooking, it might not be possible to predict them correctly for our model. Color information also isn't very helpful, because some different ingredients exactly have the same colour or same ingredients might have different colours.



hamsi: 0.58653
baklava: 0.30801
carrot cake: 0.05741
humus: 0.01253



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}
```



Green Pepper
Olive
Onion
Salami
Corn
Chicken
....

Sample projects from 2017 (BBM406)

Predicting the Location of a Photograph

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Abstract

In this paper, we addressed to prediction of an image location problem. It is still a hard problem because of several kinds of other problems. We use convolutional neural networks (CNNs) to tackle this problem. We collect data from Flickr[13], create a dataset which we call Turkey15 and test with basic algorithms. After testing the dataset, we train AlexNet and ResNet-18 with Turkey15 from scratch. Since Turkey15 is very small, we use transfer learning to improve results. We use feature extracting and fine-tuning[14]. We also freeze some layers to get better accuracy.



Figure 2: Images from Turkey15

ated a dataset which we called Turkey15 and predict image locations where is limited to Turkey.

First of all, we tested our dataset with hand-crafted features which are Tiny images, GIST features, and Hog features, because we should know that our dataset is convenient enough to use as a dataset or not. Details in this process are explained in section 3.1.

After testing the dataset, we trained existed models which are AlexNet and ResNet-18 models with our dataset. We trained from scratch in this step and get some results and compare with training with hand-crafted features. Details and result are written in section 4.1.

Thirdly, we used transfer learning, in particular, fine-tuning and feature extracting. We trained pre-trained models which are trained with places365 and imageNet datasets. Models are AlexNet and ResNet-18 again. Details are written in section 4.2.

Finally, we froze some layers of models and trained AlexNet and ResNet-18 again. Details are written in section 4.3.

2. Related Work

Because of the popularity of this challenge, there are many kinds of proposed methods and works for predicting location. Li et al. propose to represent features with SIFT and match query image features to database image features mutually[11], but matching is only among the prioritized features. They keep informative points. In this way, they reduce computational cost. We also used hand-crafted features for testing dataset, but we use convolutional neural networks for training.



Figure 1: Images from Turkey15

1. Introduction

Although there are a lot of works on this issue and it is very popular research topic in recent years, predicting the location of an image is still a hard problem. There are various problems such that constructing features [3], viewpoint problem[4], illumination and structural modification[12] etc.. It can be used for many areas such as estimation people's perception [5]. But how can we predict the location of given image? In this work, we focus on exactly the problem of city classification.

With the development of technology and the increase of applications, people are taking photos and upload to internet much more than ever. The significant point of sharing is that a huge data has existed and it can be used for creating artificial machines as an experience. At this point, we collected images from Flickr where are taken in Turkey, cre-

1

Sound of The City

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Abstract

In this paper we will introduce our project that is detects and classify leading sounds on urban sounds. We focused on audio because it was more attractive then working on image or some numerical data and also because sound is a very important tool for understanding the world. Also another reason is working with sound is very challenging because it is hard to find only one pure sound on outside world there are lots of sound sources and we generally hear the mixture of these sounds, so our data sets that we used in this project have real field records - has lots of mixed sounds. We worked on UrbanSound8K and UrbanSound data sets containing 27 hours of audio with 18.5 hours of annotated sound event occurrences across 10 sound classes (air conditioner, car horn, children playing, dog bark, drilling, engine idling, gun shot, jackhammer, siren, and street music). Our goal was to extract leading sounds with a correct shape by using Shogun and classify them correctly.

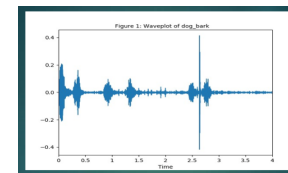
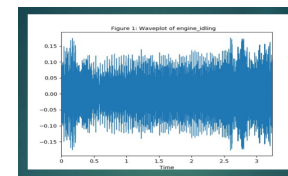
1. Introduction

Since new audio technologies developed rapidly recently, audio processing and classification are growing research fields and it contains many challenges. Especially separating audio into its components is a very tough problem. However working on an analysis of urban sounds instead of working on the analysis of speech, music, bioacoustics is relatively easy and relaxing. Furthermore we worked on extraction of the leading sounds with correct shape.

One of the main challenges in this project was lack of labeled mixed sounds. Previous work focused on classification of single labeled audio data. We needed lots of audio data to get our final results correct. With this purpose we created our own multi-labeled audios by using shogun. Actually we first wanted to separate a given kind of mixed sound into its components by using ICA (independent component analysis) but we could not find any working library or implementation of this algorithm and due to the restricted time we could not achieve this

goal. But we wanted to make it so we have done some more researches and find a new library named shogun which provide some tools for mixing and separating sounds not like ICA but it works for us to get some results by making tests on mixed sounds.

After all these things we also want to improve our results getting from tests, we decided to combine two different machine learning approach to get higher results and it was another challenge for us to increase our results by using neural networks and support vector machines combination. The approach we use to combine these two algorithms will be explained in more detail at "The Approach" section. Here you can see wave-plot form of single and mixed sound sources we worked on :



4321

Prediction Of Life Quality

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Abstract

In this study, we mention about the usage of using a machine learning approach to specify life qualities of cities instead of public research. We create an assorted dataset that contains statistical and physical features. To do that, we utilize from MAPZEN. We expect to predict the scores on MOVEHUB with high accuracy.

1. Introduction

Nowadays, we can easily see that cities differ considerably from each other in terms of their physical and social characteristics and that difference is highly influential in human life. We are making great efforts to determine the effects of these differences on human life and to make cities more livable and to change this imbalance positively.

In this situation, we are faced with a notion named quality of life.

"Quality of life (QOL) is the general well-being of individuals and societies, outlining negative and positive features of life. It involves life satisfaction, including everything from physical health, family, education, employment, wealth, religious beliefs, finance and the environment." [2]

By this definition, there are various social and physical criteria that influence the quality of life. The number of researches and studies carried out in this area is increasing day by day. While life quality information for large cities is easily accessible, it is not possible to find reliable results for cities that are not big enough.

In this project, we purpose to achieve higher efficiency in shorter time and reduce the burden on a human in such researches. Rather the laborious and time-consuming processes of public researches we also aim to provide a new, flexible and developable method by making use of

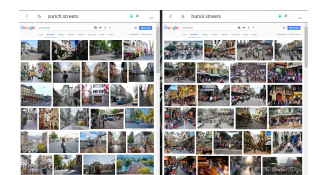


Figure 1: The reflection of the crowd difference between the Hanoi and Zurich on the street photos

machine learning experiences. Thus, we get a chance to detect the life qualities for any cities in the world. At the same time, we are expecting to be able to observe which physical factors effects the life quality with which rates.

MoVEHUB

There is a platform named MOVEHUB that helps you make informed decisions about where to move to around the world. And it has a city ranking list consists of over 200 cities. We utilized this list as the main target in the estimation results.

MAPZEN

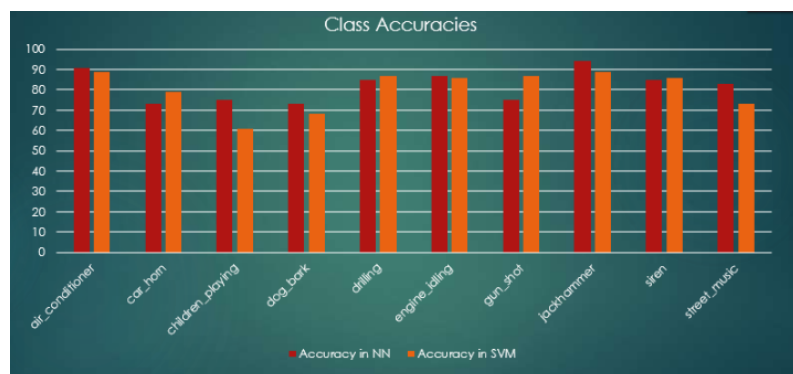
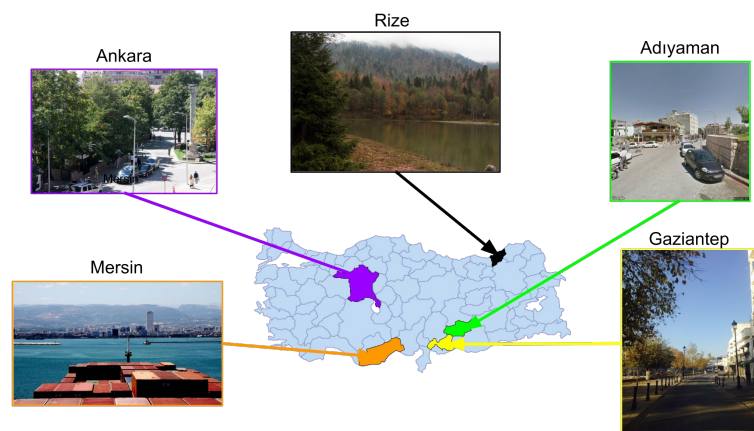
Mapzen is an open and accessible mapping platform that is focused on the core components of geo platforms, including search, rendering, navigation, and data.

2. Related Work

There are numberless researchs done to measure life quality in cities every year. In this researches generally, lots of criteria are considered to obtain correct results. Such researches have been carried out in the form of public opinion polls up to now.

MOVEHUB: MOVEHUB is similar research that includes

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Sample projects from 2018 (BBM406)

Wi-Fi Based Indoor Positioning Systems

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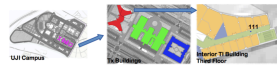


Figure 1: Source [12] Left: map of UJI campus and Tx buildings. Middle: red indicates ESTCE - Tx building. Right: example of a reference point.

Abstract

Wi-Fi Fingerprint-based positioning approach that detects the position of user or device is widely used in the indoor positioning systems instead of Global Positioning System (GPS). In this approach, Received Signal Strength (RSS) values that are known as Wi-Fi fingerprints used. Received Signal Strength values are the measurement of the power present in a received radio signals. We use UJIIndoorLoc dataset with 19937 training records and 1111 test records. This dataset of RSS values are collected by using previously placed wireless access points (WPs) in Tx Buildings of University of Jaume I campus. We aim to predict location points with respect to floor IDs, building IDs, longitude and latitude values with supervised machine learning algorithms such as K-Nearest Neighbor Algorithm, Random Forest Algorithm, Support Vector Machine and Decision Tree Algorithm. Then we use the model with the highest accuracy in the rest of the progress. Classification techniques are used for building and floor classification and regression techniques are used for detection of location points.

Keywords— indoor positioning, received signal strength indication (RSSI), machine learning algorithms, classification, random forest

1. Introduction

Global Positioning System (GPS), which uses satellites, is the most popular outdoor positioning system, however its signals can be easily blocked by various structures and factors then it becomes useless for indoor environment because of signal loss. Unlike the GPS, Indoor Positioning Systems aims to detect the position of user or device by using Access Points signal also called Wi-Fi fingerprint. With the advancing technology and spread of wireless networks, Indoor Positioning Systems become even more important place in the fields of augmented reality, social networking, personal tracking, guiding blind people, tracking small children or elderly individuals and location-based advertising etc.

Wi-Fi-based fingerprint methods have some problems when positioning phase in indoor. These problems can be caused by the fact that the devices in which the radio signals are collected during the training stage and the devices in the test phase are different.

Another reason is that the number of access points in the environment varies greatly. Inevitably, these problems negatively affect positioning success. However, we will try to determine the position with regression algorithms using the real latitude and longitude values of the collected locations.

Then we will turn our problem into classification problem by using the building and floor features in the data set. In the test section, we will try to estimate which building is located or which floor of the building.

Different machine learning algorithms will be tried and we will decide the most suitable algorithm for indoor positioning. We will use the UJIIndoorLoc database throughout the entire project. Classification and regression problems will be solved using the RSS values from 520 wireless access points (WAPs). In the classification part, since the data set contains 3 buildings, we will divide the data into three and try to estimate which floor is located.

The rest of the paper is organized as follows: Presentation of related studies, explanation of the data set used in the experiment, explanation of solution approaches, experimental results

Country Classification Using House Photos

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Abstract

Home designs vary from country to country and when we talk about housing, we should refer to both modern and traditional styles. You can come across a picture of a house taken by someone anywhere in the world and you may wonder where it has been taken from. In this project, we tried to find out which country the photo of a house was taken from. In short, we worked on the problem of classification according to where the photographs were taken.

We used our own World dataset for this project. This dataset contains over 4000 pictures for 15 different countries. In our project, we collected our data from the Flickr [1], Pinterest [3], and Google Photos [2]. We first tested our data with a single layer neural network and then with convolutional neural networks (CNN). We used ResNet18 and AlexNet models when implementing CNN in our project. In accordance with the results, we applied some methods to increase the accuracy and we got the best accuracy with ResNet18.

1. Introduction

Recognizing home photos and classifying them by country is a quite difficult problem. Because the houses in many countries in the modern world are similar to each other. Beside that, there are some features to distinguish these houses. For example, each country's climate, people's lifestyle and culture are different. This gives us some hints on the architecture of the houses in that country. From this point of view, especially the design of traditionally styled houses begins to change from a country to another. The main problem here is that the houses in the same continent are very similar to each other. For example as shown in

Figure 1, in the Asian continent, traditionally styled houses of some countries such as South Korea, Japan, Indonesia and Malaysia are very similar. This factor complicates the solution of the problem. In addition, many factors such as the shooting angle, light, shadow and seasonal differences affect the solution of this problem.



Figure 1. Example of similar data

Since this is an image classification problem, there are many algorithms and methods used in its solution. K-nearest neighbors, logistic regression, support vector machine and convolutional neural networks are some of these solutions. Especially in recent years, CNN is a successful algorithm preferred to solving problems in this area.



Figure 2. Example of similar data

In our study, we deal with the problem of classification according to the country where the house pictures were

Rock or Not?

Defne Tuncer¹ Kutay Barcin¹

Abstract

In the era of technology, millions of songs are brought to people everyday. The dramatic increase in the size of music collections has made the music genre recognition (MGR) an important task on machine learning. The goal of this paper is to give machines a chance to predict music genres. We improved our methods with model and feature selection by using k-fold cross validation afterwards. Based on the results obtained from the algorithms, we performed experimental analysis. Finally, ended our work with a detailed conclusion, and proposed our feature work.

of solvers and regularization. 4.1.3 Support Vector Machines with linear and radial basis function (RBF) kernels. 4.1.4 Deep Learning method Neural Network also known as Multi-Layer Perceptron through various optimizers. To represent the audio tracks in building our baseline models we planned to use the combination of all the features, which have been shown to be effective in the task of predicting genres. We improved our methods with model and feature selection by using k-fold cross validation afterwards. Based on the results obtained from the algorithms, we performed experimental analysis. Finally, ended our work with a detailed conclusion, and proposed our feature work.

2. Related Work

For the music genre recognition task, the most common datasets are GTZAN (Tzanetakis & Cook, 2002), Million Song Dataset (MSD) (Bertin-mahieux et al., 2011) and FMA: A Dataset For Music Analysis (Defferrard et al., 2017). While FMA, which consists of 161 sub-genres among 106,574 tracks and published in 2017, is the most up-to-date dataset, and is especially suited for MGR as it features fine genre information. A challenge took place as one of challenges of Web Conference (WWW2018) by the publishers of FMA Dataset on the subject predicting genres of the music (Defferrard et al., 2018). The winner succeeded by examining through artist-related information and scored an accuracy of 66.29% on predicting 16 genres (Kim et al., 2018).

In Music Information Retrieval (MIR), there have been various number of studies on building effective models to predict genre of music using audio features. Mel-Frequency Cepstral Coefficients (MFCCs), one of the audio features, are generally used in music genre classification as the perceptual scale of pitches of a human hearing are represented by the Mel-scale. A Hidden Markov model with MFCCs is used to classify pop, country, jazz and classical genres in (Shao et al., 2004). On the other hand, another study focuses on a new feature called Renyi Entropy Cepstral Coefficients (RECCs) (Tsai & Bao, 2010). The highest achieved accuracy scores reported on the datasets ISMIR2004 which is from the contest (Cano et al., 2006) and GTZAN are accomplished by representing the auditory human perception with a proposed spectrogram (Panagakis et al., 2009). Most of their studies are done through researching the timbre texture,

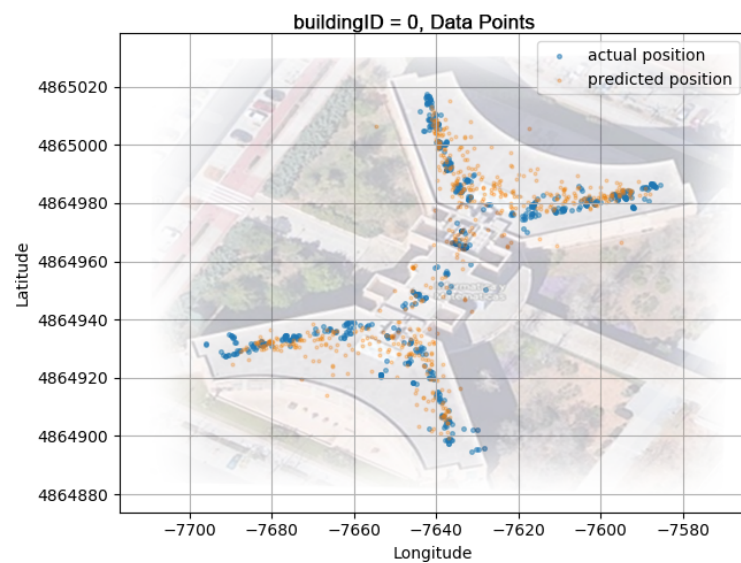
1. Introduction

When there is people, there is music. As people, living in today's world, music is always at our reach through technology. The ease of it has brought the demand of automatically generated playlists and customized music recommendations. The task in both those challenges is to be able to group songs in semantic categories. In this work, we aim to model and classify music genres with the assumption of different music genres are also different at the bit level.

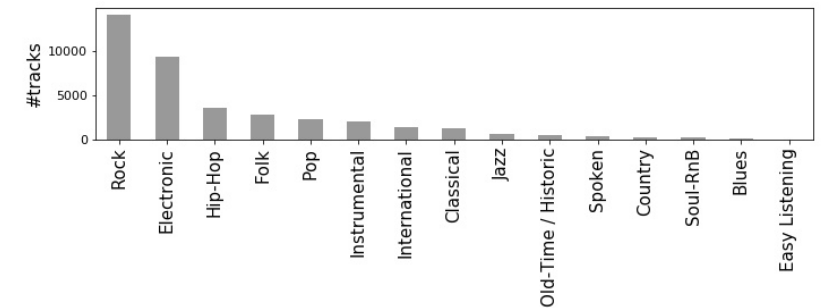
In this paper, we will put forward the efforts we made concerning the classification models that allow us to recognize the genre of a given song from its audio features. As for the beginning, we introduced studies on the subject music genre recognition. Then we made a brief introduction to the dataset we bring into use, and explained how we handled our data. Thereafter, we implemented various baseline classification models, and discussed towards advancing the models to solve the problem of music genre recognition. These methods include: 4.1.1 Nearest Neighbor Classifier with/without dimensionality reduction through Principal Component Analysis (PCA) and weighting hyperparameter. 4.1.2 Logistic Regression through one-vs-one scheme, multinomial approach and one-vs-rest scheme with variety

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Predict Class : Indonesia
Correct Class : Malaysia



Sample projects from Spring 2021 (BBM406)

Music Recommendation and Playlist Continuation

Arda Hüseyinoğlu Mehmet Serkan Tan

Abstract

In this paper, recommender systems for playlist continuation are discussed. Our approach focuses on neural network-based solutions, which have yielded immense success in many fields, for playlists that are composed of very few to many songs. The proposed approach leverages and extends the Neural Collaborative Filtering model. The model makes use of embedded vectors to find similarities between playlists. Training and evaluation are done with the 1 Million Playlist dataset which was curated by Spotify for the 2018 ACM RecSys Challenge, and it's still a relevant challenge today.

1 Introduction

In information systems, recommender systems are quite important, and a useful tool in various applications to help users in identifying relevant content in a wide database. Today, most of the music consumption is done through cloud-based streaming services (e.g. Spotify, Apple Music, Tidal). The existence of a huge number of singles on these platforms challenges consumers to compile their own tastes of music. Besides, the great size and complexity of the music data space and the subjectivity of users make the problem quite hard for the companies to recommend the right music. These concerns eventually attract many researchers that are working in the information systems.

In this work, we focus on the problem of playlist continuation, which is suggesting tracks that a user may add to an existing playlist. We build a deep learning-based playlist continuation model to tackle this problem. Our main methodology is the Neural Collaborative Filtering (NCF) proposed by [1] He et al. where they use embedding layers and multi-layer perceptron to learn user-item interaction function. We use the NCF model to adapt it our problem of playlist continuation. We also aim to extend the model by providing additional input vectors such as album-id and artist-id to learn more complex relations.

This paper is organized as follows: In the second section the related work in the field is discussed, 3rd section describes the main dataset, its characteristics and the preparation procedure for training, 4th section focuses on the

learning methodology for the model, 5th section describes the evaluation techniques to measure performance, 6th section shows, and explains the experimental findings, 7th section discusses the future work, and the concluding remarks are given at the end of the paper.

2 Related Work

In 2018, when Spotify announced the playlist recommendation competition for the first time, the top works were published in the ACM's RecSys'18 at the end of the competition. There are several approaches to consider. [2] Maksim Volkovs et al. propose a two-stage technique where in the first stage the system is optimized for fast retrieval of the music data space, and in the second stage the candidates which are retrieved in the first stage are re-ranked to maximize the accuracy for the evaluation. Making use of autoencoders and character-level convolutional neural networks is another approach[3] where they first analyze a playlist and its categorical contents and second, to make use of the playlist title. In this way, they show that popularity bias and cold start problems can be mitigated. There are also works where traditional methods are used such as [4] Sebastiano Antonucci et al. propose a solution based on content-based and collaborative models. In addition, they boost the model on top of the final prediction by analyzing the underlying structure of the dataset. (Spotify 1 Million Playlist). They also look out for computational resources. Also, [5] Vasilij Rubtsov et al. applies collaborative filtering for the candidate selection, and gradient boosting for final prediction.

Besides the RecSys'18 publications, [1] He et al. proposed an alternative way for the collaborative filtering. They use multi-layer perceptron to learn the user-item interaction function to generalize matrix factorization under its framework. They use two feature vectors as input to describe a user and an item. Since the proposed work based on the collaborative filtering setting, identity of a user and an item are used as the input feature which is a kind of one-hot encoded vector. Embedding layers are used to project the sparse representation of the input vectors to a dense vector. Then, the user embedding and item embedding are then fed into a multi-layer neural architecture, which they are called as

Art-Style Image Transferring

Oktaý UĞURLU* Koray KARA* Ahmet Deniz GÜNER*

Abstract

Nowadays, Generative Adversarial Networks (GANs) are an emerging technology that is used in both supervised and unsupervised learning. These networks are also capable of producing high-quality data in an efficient way. Image to image translation is one of the core applications of GANs. For instance, a data augmentation that we have used in this project. In this study, we propose the methods that keep the quality of the style transferring high. For this purpose, we are using the CycleGAN that is an extension of the GAN architecture. Generative Networks allow easy mapping between the source image and the target image. It also calculates a loss function to greatly improve the quality of this generated target image. These models are often used to transfer the styles of famous artists to today's paintings. However, GAN modules work with very large data sets. This can cause the training time of the model to increase too much. All pictures of these artists are usually inserted into the model as a train set. In this study, we discussed the possibility of having more than one style in the paintings of the artist to be transferred in style and this situation may affect the model. We examined the effects of this situation on the cycle-GAN model. In our study, we compared the models trained with the whole data set, with the data entering this model trained with clusters after clustering. We used the K-means model and feature extraction methods to cluster the data set. We observed how clustered data affect the success of generative art models, and we aimed to reduce the training times of the models since we use smaller data sets.

1. Introduction

A lot of work has been done in the field of computer vision so far. Image to image translation is one of the core tasks in that area in a way that one of the source images is translated to the target image while keeping the originality of the source image. For this specific purpose of task, Generative Adversarial Network (GAN) is a helpful idea for

image to image translation. These networks are actually a combination of two networks that are Generator and Discriminator. We are using CycleGAN (Zhu, Park, Isola, and Efros, 2017) that is a technique for training unsupervised image translation by using GAN architecture for unpaired image-to-image translation. A CycleGAN is composed of 2 GAN's. That means a CycleGAN has 2 generators and 2 discriminators in total. One of the generators takes the images as an input from first dataset, and outputs images for the second dataset. After that, the other generator takes images from the second domain as input and generates images for the purpose of the first domain. Discriminator models are used to determine how appropriately generated images are created and update generator models according to these determinations. In this project, we are also using an additional extension of the CycleGAN that is called cycle consistency loss. This is essentially based on the purpose that the image output of the first generator can be used as the input of the second generator and that the output of this generator also matches the original image. For this purpose, we have calculated the cycle consistency in order to find the differences between real photos as input and transformation of generated Van Gogh images by using the input. Then, we have used the loss values in the calculation of the gradient.

We trained the cycle-Gan model with clustered datasets instead of skewing with the whole dataset and observed the results. Here are the expected results from observations; When we cluster structural as structural, it is better to transform a test picture of that struct; If an artist has more than one style, we can aggregate them based on styles to get better output from GAN and to reduce the training time of the model as we shrink the datasets. In order to do these clustering operations, we had to extract features from the train set we have. We used VGG19 feature extraction methods to do this. VGG is basically a convolutional neural network model. The numbers 19 represent how many convolutional layers there are in the model. This structure is generally used for image object classification (Rashid, Khan, Alhaisoni, Wang, Naqvi, Rehman, and Saba, 2020). In our study, we tried to use these VGG layers for both object-based classification and style-based classification. We have run the K-means clustering method on the features we obtained from feature extraction. With the clusters we obtained, we trained our GAN models and observed the results. K-means is basically

Tune It Up: Music Genre Transfer and Prediction

Fidan Samet¹ Oguz Bakir¹ Adnan Fidan¹

Abstract

Deep generative models have been used in style transfer tasks for images. In this study, we adapt and improve CycleGAN model to perform music style transfer on Jazz and Classic genres. By doing so, we aim to easily generate new songs, cover music to different music genres and reduce the arrangements needed in those processes. We train and use music genre classifier to assess the performance of the transfer models. To that end, we obtain 87.7% accuracy with Multi-layer Perceptron algorithm. To improve our style transfer baseline, we add auxiliary discriminators and triplet loss to our model. According to our experiments, we obtain the best accuracies as 69.4% in Jazz to Classic task and 39.3% in Classic to Jazz task with our developed genre classifier. We also run a subjective experiment and results of it show that the overall performance of our transfer model is good and it manages to conserve melody of inputs on the transferred outputs.

1. Introduction

"Music is the food of soul," said Arthur Schopenhauer. Music is an art that appeals to everyone. People have particular interest in music of certain genres such as Jazz, Pop, and Classic. By performing music genre transfer, music from different genres can be transferred to a certain genre. Thus, new hit songs can be generated automatically, musicians can easily cover music of different genres, and the music arrangements required in this process can be reduced. By music genre prediction, the performance of music genre transfer methods can be assessed. Furthermore, recommendations can be made to the listeners based on their favorite music genres. Thus, companies can obtain more profit with useful and accurate recommendations.

Style transfer between different domains has become a hot topic in the machine learning research field. Many deep

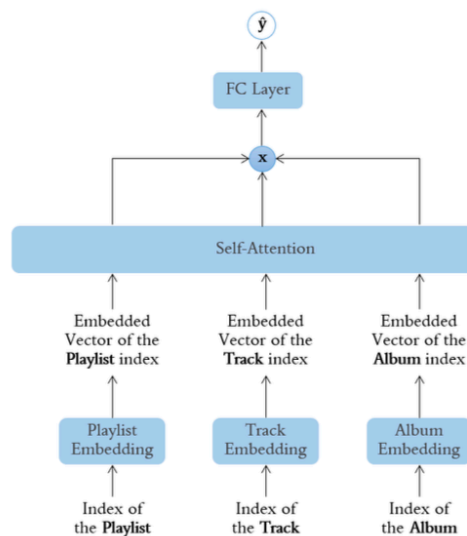
learning methods have been developed to accomplish this task. By extracting fundamental knowledge about domains with obtaining deep comprehensions, deep learning models can perform style transfer. Therefore deep generative models like Generative Adversarial Networks (GAN) (Goodfellow et al., 2014) perform well in style transfer. Pioneering works have been done especially in the image domain, so that transforming images of summer to winter, night to day and photos to certain painter's drawings can be done successfully. In this project, we focus on style transfer in the music domain.

There are several music datasets in the literature. However, lyrics and various instruments are mixed in some of them. To perform music genre transfer, these variants must be separated from each other. Therefore, due to time issues, we consider a music dataset containing only piano as an instrument. We work on transferring these symbolic music from source to target music genre domain. Hence, we use one of the state-of-the-art deep learning methods, CycleGAN (Zhu et al., 2017) which performs unpaired image-to-image translation using cycle consistent adversarial networks, as our baseline. After adapting CycleGAN framework to music domain, we improve our baseline by adding auxiliary discriminators and triplet loss. Thus, we perform music genre transfer so that melody of the source genre retains while note pitches change according to the target genre. To assess the performance of the model, we perform genre prediction on the transferred music and check the classification accuracy according to the target domain. To that end, we test several machine learning classification algorithms and choose Multi-Layer Perceptron classifier, which gives the best accuracy. Since it is a challenging task to evaluate transfer methods, we also run a subjective experiment.

2. Related Work

(Brunner et al., 2018) introduces a method to perform music genre transfer on three major musical styles which are Jazz, Classical and Pop, by adapting CycleGAN model. They create and use a dataset consisting of MIDI (Musical Instrument Digital Interface) files. They introduce additional discriminators and classifiers to their CycleGAN-adapted approach. They train separate classifiers and transfer models for music genres. Their overall performance in both tasks is

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Sample projects from Fall 2022 (AIN311)

Project LEAFS: Learning Efficiency Assessment from Footage of Students

Abdullah Enes Ergun¹ Baha Kirbasoglu¹ Can Ali Ates¹

Abstract

Attitudes of the students in class affect lecture efficiency for both the lecturer and themselves. Keeping track of each student's attitude simultaneously during lecture is a really hard problem. Therefore, we propose a method to detect different attitudes of students for solving this problem in this case study. We use the YOLOv5 tool that combines deep learning and computer vision techniques. For instance, Convolutional Neural Networks. We collected our dataset using web scraping, taking classroom photos by hand and using a small portion of dataset which is available online. The dataset which is collected from the multiple sources contains seven classes. These classes are separated into three positive and four negative classes. We created a semi-theoretical formula based on these classes that calculates lecture efficiency according to detected class instance counts and weights of these classes. While positive classes increase the efficiency during lecture efficiency assessment, on the other hand, negative labels decrease. Our goal is to help lecturers to improve their lectures, based on students' attitudes.

1. Introduction

Most of the time, assessing the efficiency of a lecture for students is a problem for the lecturer. The lecturer cannot be sure if the lecture is understandable or not. In this situation, the lecturer needs a simultaneous system to keep track of the students one by one based on their attitudes. Students can act different behaviours during the lecture such as playing phone, taking notes, sleeping, etc. These attitudes can have different meanings. For instance, a student who yawns is not completely distracted from lecture, can still listen the lecture without hundred percent attention. The lecturer cannot assess all of these attitudes in real-time during a lecture, so an automated system has to detect students' attitudes and evaluates the status of the student based on what the student does. Therefore, developing a system that calculates the lecture efficiency based on semi-theoretical formula that created by ourselves with giving weights to these student attitudes and then reports the calculated lecture efficiency

with detected student attitudes in class both visually and written to the lecturer in real time may help both the students and the lecturer. This developed system is supported with graphical user interface. In other words GUI, that is designed by us to create user friendly environment. Lecture efficiency basically can be assessed with seven attitudes. These attitudes can be evaluated as positive and negative. While positive attitudes such as listening, taking notes and raising a hand increase lecture efficiency; on the other hand, negative attitudes such as yawning, playing with the phone, sleeping and eating or drinking something can decrease lecture efficiency. Weights of these attitudes are determined by us scaled into zero-one range. The algorithm that we use assesses the lecture efficiency and returns a basic report to a lecturer to prevent inefficient lectures. As a result of these reports, the lecturers can change their own teaching techniques or materials, and students can focus more with these improvements then change their own behaviours.

2. Related Work

Assessing student attitudes is a rare research topic that we found a few articles about. There are several articles use different techniques to detect behaviour of students. Article¹ collects their own data from classroom videos like we made. After that, combines the temporal and action detection to create recognition model. Then, uses this recognition model for task recognition. It uses the recognition results by giving these results to different type of video captioning models such as, HACA and RecNet. This study had some troubles like ours such as misclassifications and lack of dataset. For instance, model detects reading book as playing with phone or vice versa. So, some of the misclassification occurs because of the perspective. This study provides us a perspective to detect student behaviours and misclassifications in different way, so this article can use for the future directions of our model. Article^{2,3,4} is about detection systems to detect mobile phone usage of a person with using classical Convolutional Neural Network and Faster Region Based Convolutional Neural Network. Article⁵ uses mAP@0.5 as the evaluation metric. This studies, give us an approach about detection of behaviours which can be identified by pairing another tool such as taking note detection with pencil and notebook, playing phone detection with phone, eating or drinking detection with foods and beverages. Also, ex-

Question Assistant Barlas

Mehmet Berat ERSARI Zeynep Hafsa Dilmaç

Abstract

We need machine learning techniques to automatically generate questions from educational materials such as textbooks and articles. This is an important problem in education because it can help students better understand and retain the material they are learning. In order to generate questions, an education AI system must be able to understand the underlying concepts and ideas presented in the material, as well as the appropriate level of difficulty for the questions. Research in this area is ongoing and aims to develop algorithms and models that can generate high-quality questions that are both challenging and relevant to the material being studied. In this project, we realize question generation, which we think will be very useful in the field of education. We use mT5 (Xue et al., 2021) models while executing this artificial intelligence problem. While approaching this problem, our passion and the main goal is to produce Turkish questions from Turkish texts. We find TQquad (TEKNOFEST, 2018) dataset, which we used and fine-tuned, from Teknofest's website before. We get the listed scores after fine-tuning on mT5 small and base model. The best results we have got in mT5-base for 20 epochs; BLEU-1 0.24, BLEU-2 0.31, BLEU-3 0.38, BLEU-4 0.42, ROUGE-1 0.43, ROUGE-L 0.44, METEOR 0.32.

1. Introduction

We are embarking on a project to create a question-generation model, which is a basic problem in the field of artificial intelligence. This project was interesting because in our opinion, one of the most important areas of artificial intelligence is NLP. Artificial Intelligence needs to be able to understand and interpret human language. This requires deep learning models. In order to train this model to accurately generate questions, we need a large amount of labeled data in the form of paragraphs with related questions. Our goal is to develop a system that can predict a relevant question based on a given paragraph in Turkish. While there is a wealth of training data available in English, such as the WebQuestions dataset (Talmor & Berant, 2018). Most of the research in this area has focused on the English language.

Therefore, we face the challenge of generating questions in Turkish, which is a language with limited resources and research in the field of question generation. Despite this, we have managed to locate a dataset that we believe will be sufficient for our needs, and we plan to use it to train our model. In order to choose the most suitable models for this task, we are reviewing the various models that have been used for NLP and question generation, and selecting the ones that we think will be the most effective for our project. These include mBERT (Devlin et al., 2018b) and mT5 (Xue et al., 2021), which are newer models that have been widely used and have demonstrated strong performance in a variety of NLP tasks. In most studies they generate a question by giving a paragraph and an example answer. However, we fine-tuned the model just using paragraphs and questions. The model we obtained, predicts a random question with given paragraph. Since we can not find a study that uses a similar approach to us. We confused on the evaluation of the model. We have reference questions and we have a random predicted question. We measure the similarities between generated question and reference questions. And then, we assumed the score of the generated question as maximum score of that comparisons.

2. Related Work

When text generation is researched as a topic, it is seen that there are different subjects in this field and many studies on these subjects. In a study conducted in 2022, a text generation study was carried out to increase text classification (Bayer et al., 2022). In another recent study conducted in 2022, a text summary study was conducted for Italian texts and good results were obtained with BART-IT model (La Quatra & Cagliero, 2022) Many more such examples can be found. If we narrow the subject a bit, a lot of work has been done on question generation and question answering. In the past, it has focused more on answering questions and therefore question answering studies are more than question generation studies. Question generation has been a somewhat more up-to-date subject of study. Question answering, on the other hand, still has current studies. In the study conducted in 2022, question answers were created from Dutch texts using the BERT model (de Jong & Bouma, 2022). Finally, when the question generation studies, which is our subject, are examined, it is seen that in a study conducted in 2020, question generation was made from the texts, the

Career Path Predictor

Melike Nur Dulkadir, Sare Naz Ersoy

Abstract

Choosing a career path in computer science is an important decision that can have a significant impact on every individual future. A career in computer science offers many exciting and rewarding opportunities, as well as the potential for high salaries and job security. However, it is also a field that is constantly evolving and requires ongoing learning and development. There are many different fields and specialties within computer science. Each of these fields requires a different set of skills and knowledge, and it is important to choose a path that aligns with your interests and strengths. With this in mind, we have developed a career path recommendation system as a solution to this problem. This program utilizes various machine learning techniques, including Gradient Boosting, AdaBoost, and Neural Network, to recommend career paths by combining two datasets. The larger of these datasets currently contains 20000 rows and 39 columns. Our aim is to provide helpful career path recommendations to users.

1. Introduction

It has become common for students to select their career paths based on the choices of their friends or the friend that offer the highest salaries rather than considering their strengths. This approach often leads to disappointment and disillusionment. Additionally, when hiring candidates, recruiters must evaluate them on various factors. Therefore, there is a need for a system that can assist students in choosing a job role that is well-suited to their skillset and other evaluation criteria, which can now be achieved through the use of machine learning techniques. A career path recommendation system is a tool that uses data and algorithms to suggest potential career paths based on an individual's interests, skills, and experience. These systems can be incredibly useful for individuals who are unsure of what they want to do with their careers, who are looking to make a change but are not sure where to start. By analyzing data on job demand, salary, and other factors, a career path recommendation system can provide tailored recommendations that can help

individuals make informed decisions about their careers. In this article, we will explore how these systems work.

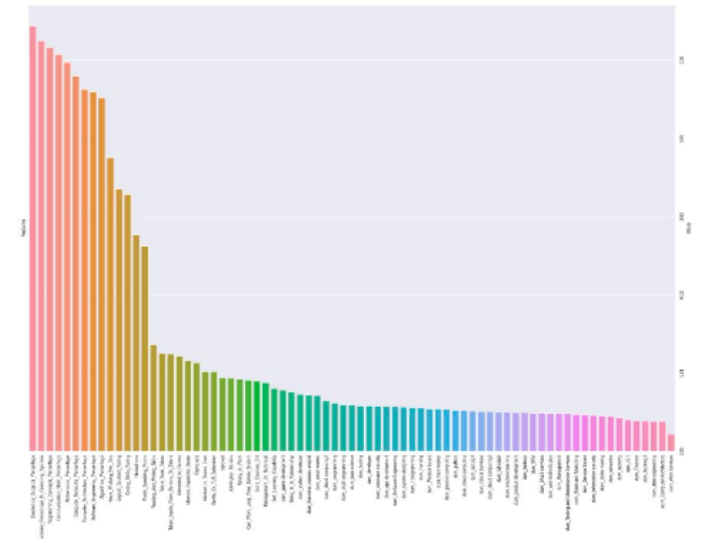
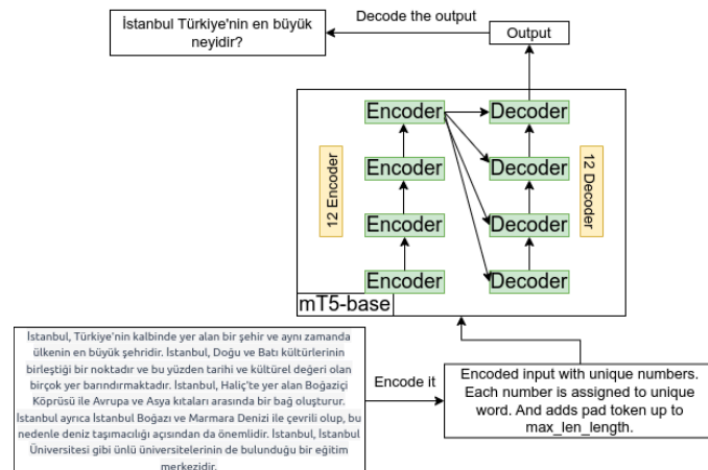
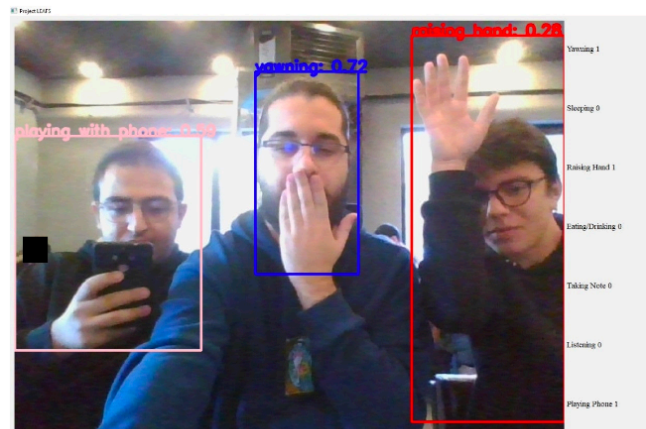
2. Related Works

The selection of a career path is a crucial decision that can have a significant impact on an individual's future. Therefore, numerous studies have been conducted on this topic. In this review, we examined four studies that focused on predicting future career paths using machine learning techniques.

The first of the articles containing studies similar to our project is Skill-based Career Path Modeling and Recommendation, created by Aritra Ghosh, Beverly Woolf, Shlomo Zilberstein, and Andrew Lan (1). In this article, the Monotonic Nonlinear State-space Model was created using real-world datasets (LinkedIn and Indeed) to analyze online user professional profiles and provide users with actionable feedback and recommendations on how to achieve their career goals. This model offers users a path that includes intermediate steps to achieve the purpose they specify.

The second article is A Machine Learning Approach for Future Career Planning, created by Stanford University students Yu Lou, Ran Ren, Yiyang Zhao (2). In this study, each person's profile and career path are considered as a sequence containing more than one node, and each node is represented by various polynomial features (vi1, vi2, ..., vik). Considering a person's current career path and goal, it is aimed to propose the most appropriate career path, that is, the path with the highest probability of reaching the target node, using the Markov Chain model. In addition, the K-means clustering algorithm is used to group many semantically similar algorithm headers.

The third article, which we consider as the primary example for our study, is the article titled Computer Science Career Recommendation System Using Artificial Neural Network by Brijmohan Daga, Juhi Checker, Anne Rajan, Sayali Deo (3). The dataset used in this study is the same as the dataset of our main study that we used when presenting our first proposal. In this article, using 20000 observations, academic percentages, and extra & co-curricular activities, various vocational suggestions are made for people according to their various characteristics such as activities and personal choices. An artificial neuron network (ANN) model was



Collaboration Policy

- All work on assignments have to be done **individually**. The course project, however, can be done **in pairs**.
- You are encouraged to discuss with your classmates about the given assignments, but these discussions should be carried out in an abstract way.
- **In short, turning in someone else's work, in whole or in part, as your own will be considered as a violation of academic integrity.**
- Please note that the former condition also holds for the material found on the web as everything on the web has been written by someone else.

<http://www.plagiarism.org/plagiarism-101/prevention/>

Course Outline

- **Week1** Overview of Machine Learning, Nearest Neighbor Classifier
- **Week2** Linear Regression, Least Squares
_____ *Assg1 out*
- **Week3** Machine Learning Methodology
- **Week4** Statistical Estimation: MLE, MAP, Naïve Bayes Classifier
_____ *Assg1 due*
- **Week5** Linear Classification Models: Logistic Regression, Linear Discriminant Functions, Perceptron
_____ *Assg2 out*
- **Week6** Neural Networks
_____ *Course project proposal due*
- **Week7** Deep Learning
_____ *Assg2 due*

Course Outline (cont'd.)

- **Week8** Support Vector Machines (SVMs), Multi-class SVM
- **Week9** *Midterm Exam*
_____ *Assg3 out*
- **Week10** Kernels, Support Vector Regression, Decision Tree Learning
- **Week11** Ensemble Methods: Bagging, Random Forests, Boosting
_____ *Assg3 due*
- **Week12** Clustering: K-Means Clustering, Spectral Clustering, Agglomerative Clustering
_____ *Project progress report due*
- **Week13** Dimensionality Reduction: PCA, SVD, ICA, Autoencoders
Course Wrap-up, Project Presentations
- **Week 14** Project Presentations
_____ *Final project report due*

Machine Learning: An Overview

Quotes

- *“If you were a current computer science student what area would you start studying heavily?”*
 - *Answer: Machine Learning.*
 - *“The ultimate is computers that learn”*

– Bill Gates, Reddit AMA
- *“Machine learning is today’s discontinuity”*

– Jerry Yang,
Co-founder, Yahoo
- *“AI is the new electricity! Electricity transformed countless industries; AI will now do the same.”*

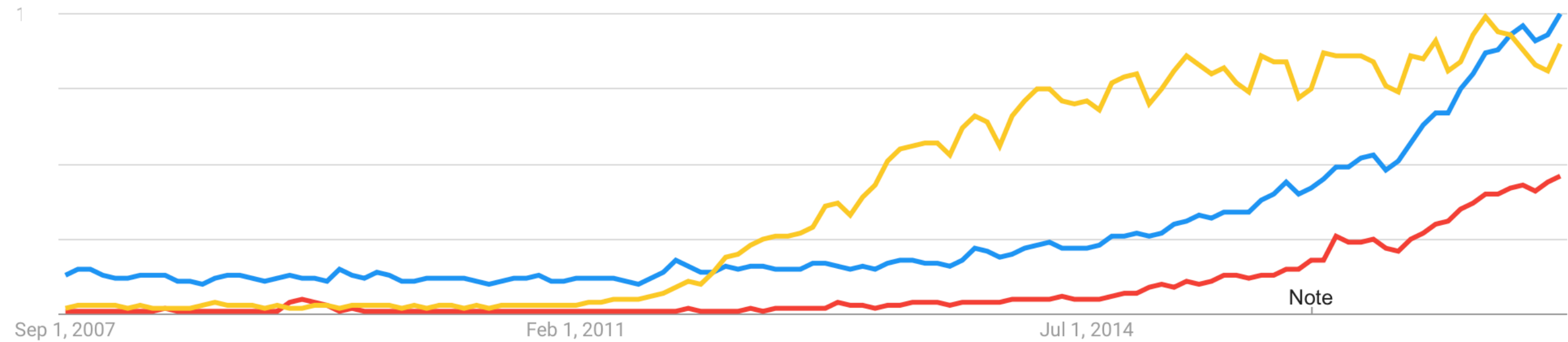
– Andrew Ng

Google Trends

● Machine learning
Field of study

● Deep learning
Field of study

● Big data
Topic



Note

CORE TECHNOLOGIES

ARTIFICIAL INTELLIGENCE 	DEEP LEARNING 	MACHINE LEARNING 	NLP PLATFORMS 	PREDICTIVE APIS 	IMAGE RECOGNITION 	SPEECH RECOGNITION
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RETHINKING ENTERPRISE

SALES 	SECURITY / AUTHENTICATION 	FRAUD DETECTION 	HR / RECRUITING 	MARKETING 	PERSONAL ASSISTANT 	INTELLIGENCE TOOLS
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RETHINKING INDUSTRIES

ADTECH 	AGRICULTURE 	EDUCATION 	FINANCE 	LEGAL 	MANUFACTURING 	MEDICAL
OIL AND GAS 	MEDIA / CONTENT 	CONSUMER FINANCE 	PHILANTHROPIES 	AUTOMOTIVE 	DIAGNOSTICS 	RETAIL

RETHINKING HUMANS / HCI

AUGMENTED REALITY 	GESTURAL COMPUTING 	ROBOTICS 	EMOTIONAL RECOGNITION
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SUPPORTING TECHNOLOGIES

HARDWARE 	DATA PREP 	DATA COLLECTION
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AGENTS

PROFESSIONAL	PERSONAL	OS INTERFACES

AUTONOMOUS SYSTEMS

AIR	GROUND	SEA	INDUSTRIAL

ENTERPRISE

SECURITY / FRAUD	HR / RECRUITING	SALES	MARKETING	CUSTOMER SUPPORT	INTERNAL INTEL	MARKET INTEL

PLATFORMS

RESEARCH / AGI	FULL STACK	MACHINE LEARNING	INDUSTRIAL IOT	AUDIO	VISION	DATA ENRICHMENT

INDUSTRIES

ADTECH	AGRICULTURE	FOR GOOD	RETAIL FINANCE	LEGAL	MATERIALS & MFG	HEALTHCARE

INDUSTRIES (CONT'D)

EDUCATION	TRANSPORT & LOGISTICS	INVESTMENT FINANCE	DATA SCIENCE	MACHINE LEARNING	OPEN SOURCE

ENTERPRISE INTELLIGENCE

VISUAL Orbital Insight planet clarifai DEEP VISION cortica IgoCion SPACE_KNOW Captricity netra deepomatic	AUDIO Gridspace TalkIQ nexidia twilio CAPIO Expect Labs Clover Mobvoi Quirious.AI popUP archive	SENSOR PREDIX IoT MAANA Sentenai PLANET OS UPTAKE IMUBIT Preferred Networks thingworx KONUX Alluvium	INTERNAL DATA PRIMER IBM WATSON Cycorp Palantir ARIMO Alation Sapho Outlier Digital Reasoning	MARKET mattermark Quid DataFox PREMISE Bottlenose MOTIVA enigma CB INSIGHTS Tracxn predata
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ENTERPRISE FUNCTIONS

CUSTOMER SUPPORT DigitalGenius Kasisto ELOQUENT Wise.io ACTIONIQ zendesk Preact CLARABRIDGE	SALES collective[i] sense fuse machines AVISO salesforce INSIDE SALES .COM clari Zensight	MARKETING MINTIGO Lattice RADIUS LiftIgniter [PERSADO] brightfunnel retention SCIENCE COGNICOR AIRPR msg.ai	SECURITY CYLANCE DARKTRACE ZIMPERIUM deepinstinct Sentinel DEMISTO graphistry drawbridge SignalSense AppZen	RECRUITING textio entelo Wade & Wendy hiQ unifi SpringRole GIGSTER HireVue
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AUTONOMOUS SYSTEMS

GROUND NAVIGATION drive.ai AdasWorks ZOOX MOBILEYE UBER Google TESLA nuTonomy Auro Robotics	AERIAL SKYDIO SHIELD AI Airware DJI LILY DroneDeploy pilot.ai SKYCATCH	INDUSTRIAL JAYBRIDGE OSARO CLEARPATH ROBOTICS fetch ROBOTICS KINDRED HARVEST AUTOMATION rethink robotics	PERSONAL amazon alexa Cortana Allo facebook Siri Replika	PROFESSIONAL butter.ai pogo SKIPFLAG clara x.ai slack talla Zoom sudo
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INDUSTRIES

AGRICULTURE BLUE RIVER mavrx tule TRACE GENOMICS Pivot Bio TerraAvion AGRI-DATA Descartes Labs udi abundant ROBOTICS	EDUCATION KNEWTON volley gradescope CTI coursera UDACITY alt school	INVESTMENT Bloomberg sentient ISENTIUM KENSHO alphasense Dataminr CEREBELLUM CAPITAL Quandl	LEGAL blueJ BEAGLE Everlaw RAVEL seal ROSS LEGAL ROBOT	LOGISTICS NAUTO Acerta PRETECKT Routific clearmetal MARBLE PITSTOP
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INDUSTRIES CONT'D

MATERIALS zymergen Citrine Eigen Innovations SIGHT MACHINE GINKGO BIOWORKS nanotronics CALCULARIO	RETAIL FINANCE TALA zest finance Lendo earnest affirm MIRADOR wealthfront Betterment
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HEALTHCARE

PATIENT PULSE CareSkore ZEPHYR HEALTH IBM Watson Health Oncota SENTRIAN Atomwise Numerate	IMAGE BUTTERFLY 3SCAN ARTERYS enlitic BAYLABS imagia Google DeepMind	BIOLOGICAL iCarbonX color GRAIL deep genomics RECURSION LUMINIST Numerate Atomwise verily WHOLE BIOME
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TECHNOLOGY STACK

AGENT ENABLERS
 OCTANE.AI howdy Maluuba KITT.AI
 OpenAI Gym Kasisto AUTOMAT
 semanticmachines

DATA SCIENCE
 DOMINO SPARKBEYOND rapidminer
 kaggle DataRobot yhat AYASDI
 data iku seldon yseop bigml

MACHINE LEARNING
 CognitiveScale GoogleML context relevant
 Cycorp HyperScience nora logics minds.ai H2O.ai
 SCALED INFERENCE sparkcognition loop GEOMETRIC INTELLIGENCE
 deepsense.io reactive skymind bonsai

NATURAL LANGUAGE
 agolo #FYLIEN LEXALYTICS
 Narrative Science loop@ai spaCy LUMINOSO
 cortical.io MonkeyLearn

DEVELOPMENT
 SIGOPT HyperOpt fuzzyio okite
 rainforest lobe Anodot
 Signifai LAYER 6 AI bonsai

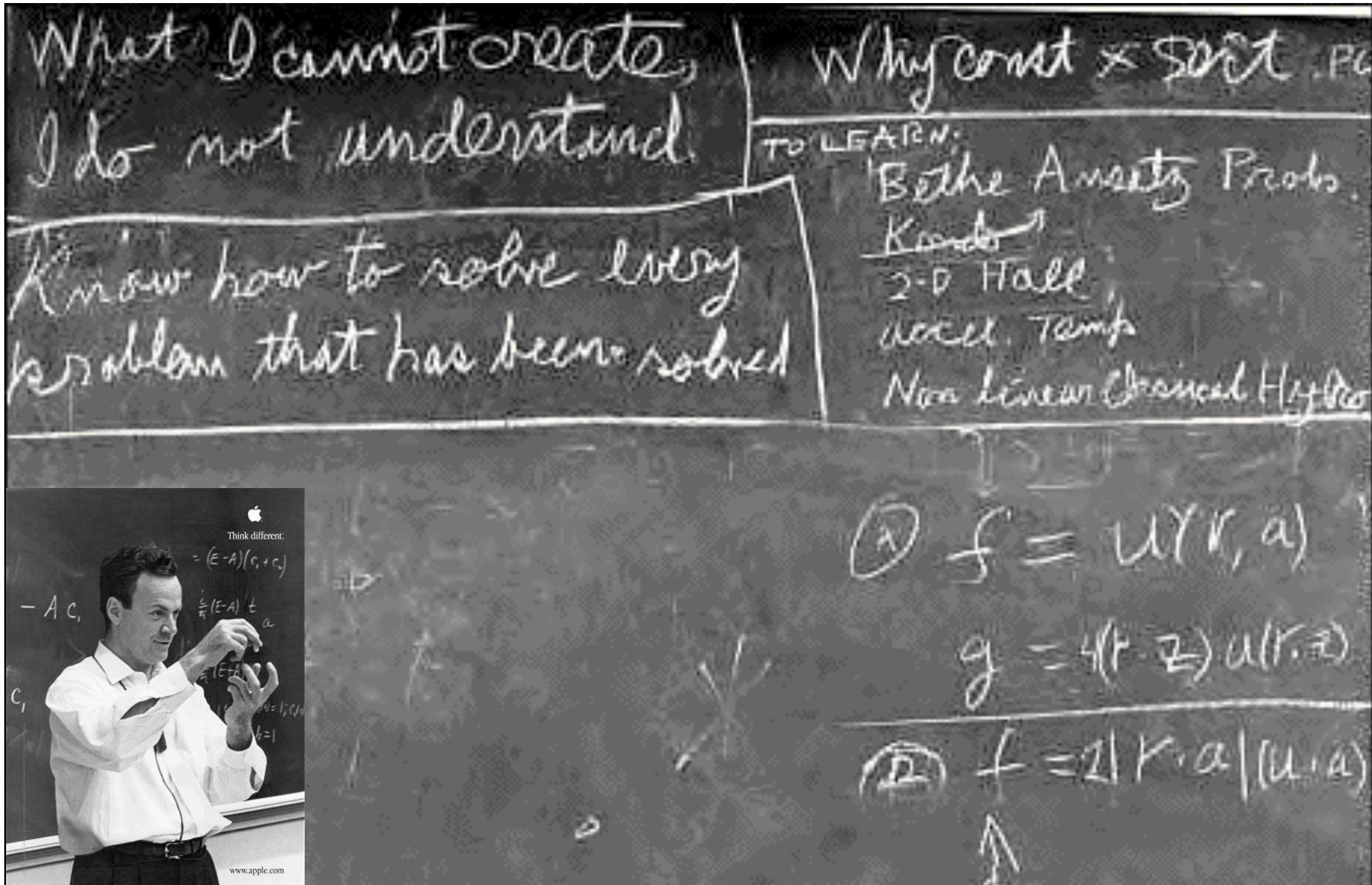
DATA CAPTURE
 CrowdFlower diffbot CrowdAI import io
 Paxata DATASIFT amazon mechanical turk enigma
 WorkFusion DATALOGUE TRIFACTA parsehub

OPEN SOURCE LIBRARIES
 Keras Chainer CNTK TensorFlow Caffe
 H2O DEEPLARNING4J theano torch
 DSSTNE Scikit-learn AzureML neon
 MXNet DMTK Spark PaddlePaddle WEKA

HARDWARE
 KNUPATH TENSTORRENT Cirrascale
 NVIDIA intel nervana Movidius
 tensilica GoogleTPU 10²⁶ Labs Qualcomm
 Cerebras Isosemi

RESEARCH
 OpenAI nnaisense ELEMENT AI vicarious
 KNOGGIN Numenta Kimera Systems Cogital

Learning



Richard Feynman

Two definitions of learning

(1) Learning is the acquisition of knowledge about the world.

Symbolic approach *Kupfermann (1985)*

(2) Learning is an adaptive change in behavior caused by experience.

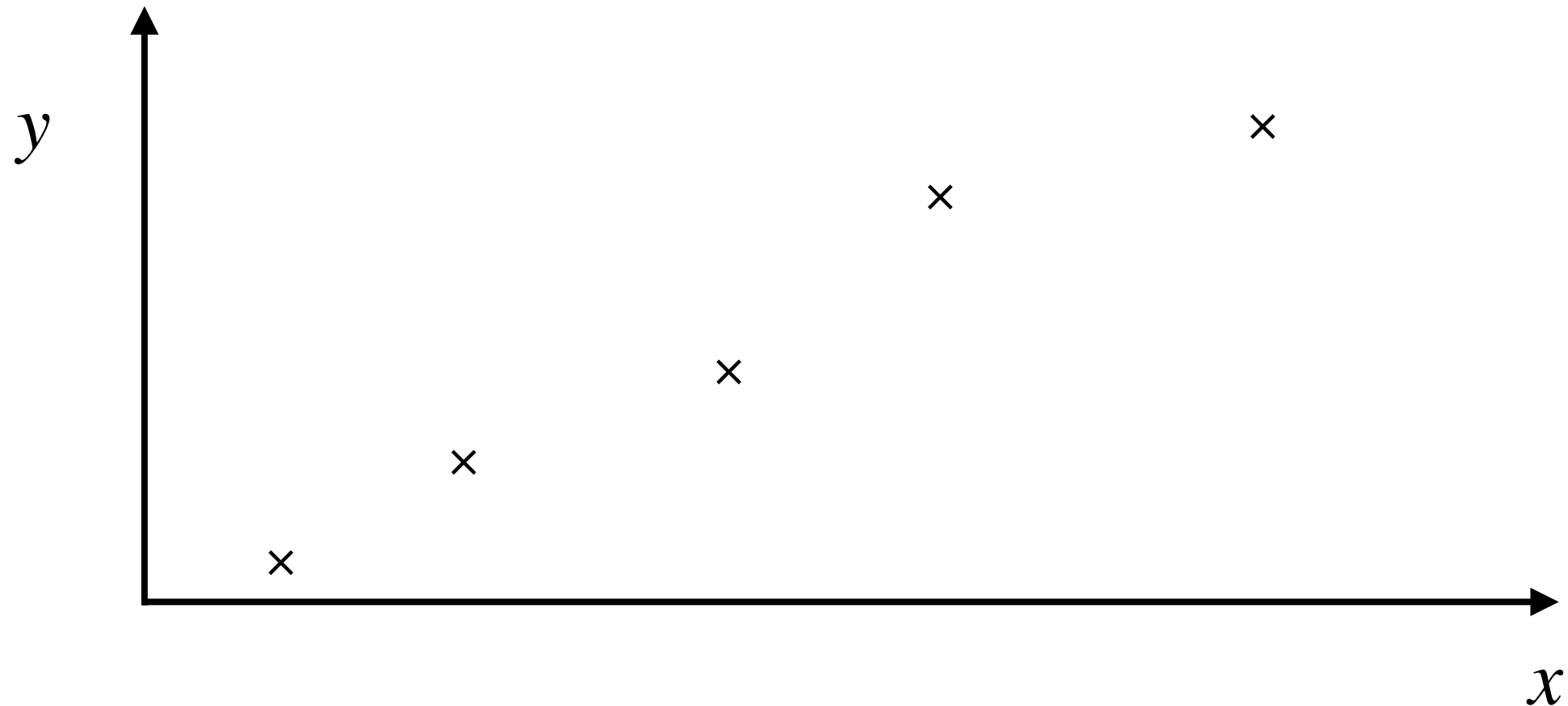
Connectionist approach *Shepherd (1988)*

Empirical Inference

- Drawing conclusions from empirical data (observations, measurements)

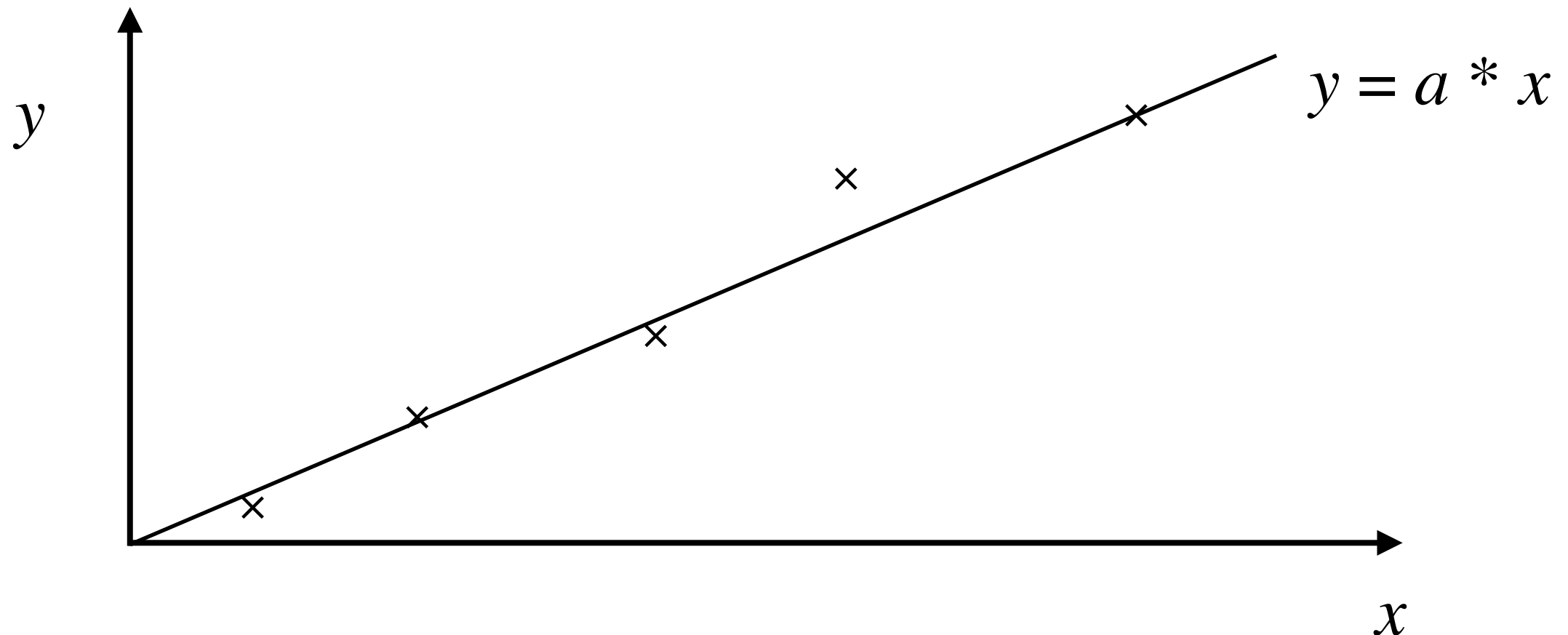
Empirical Inference

- Drawing conclusions from empirical data (observations, measurements)
- Example 1: scientific inference



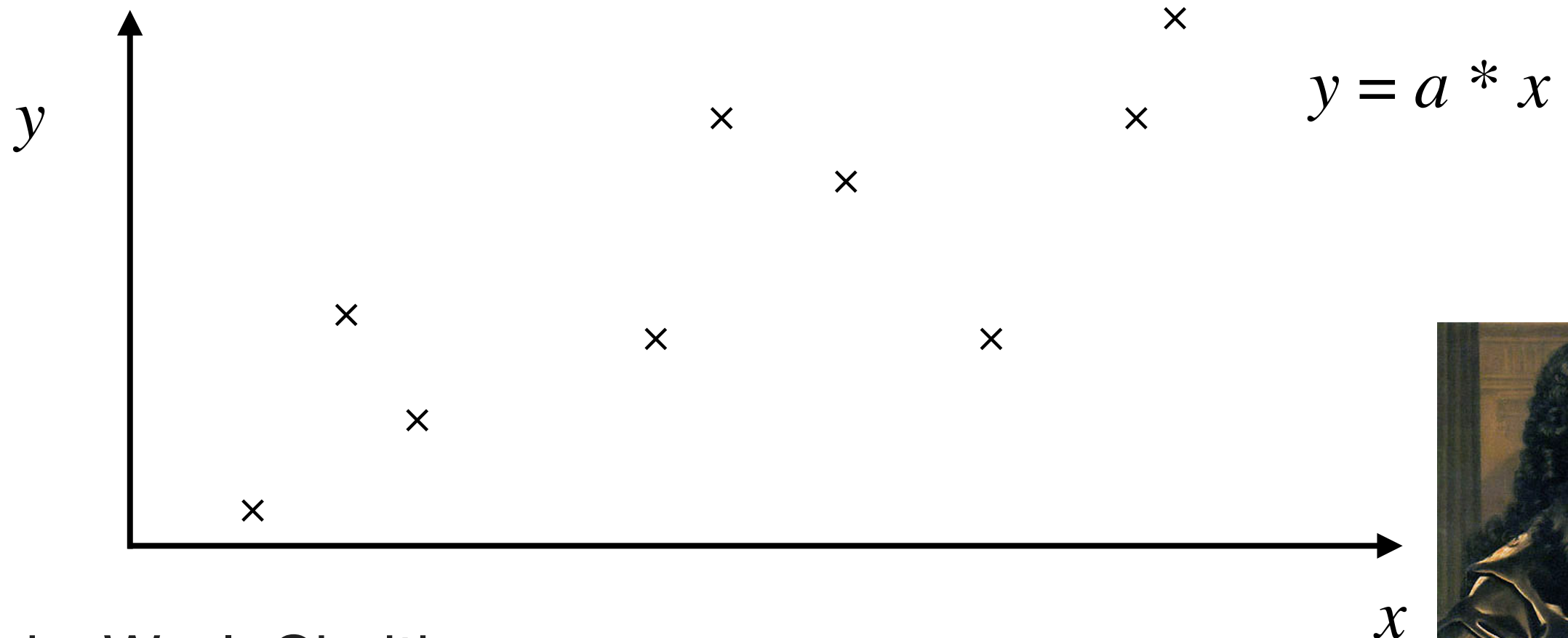
Empirical Inference

- Drawing conclusions from empirical data (observations, measurements)
- Example 1: scientific inference



Empirical Inference

- Drawing conclusions from empirical data (observations, measurements)
- Example 1: scientific inference

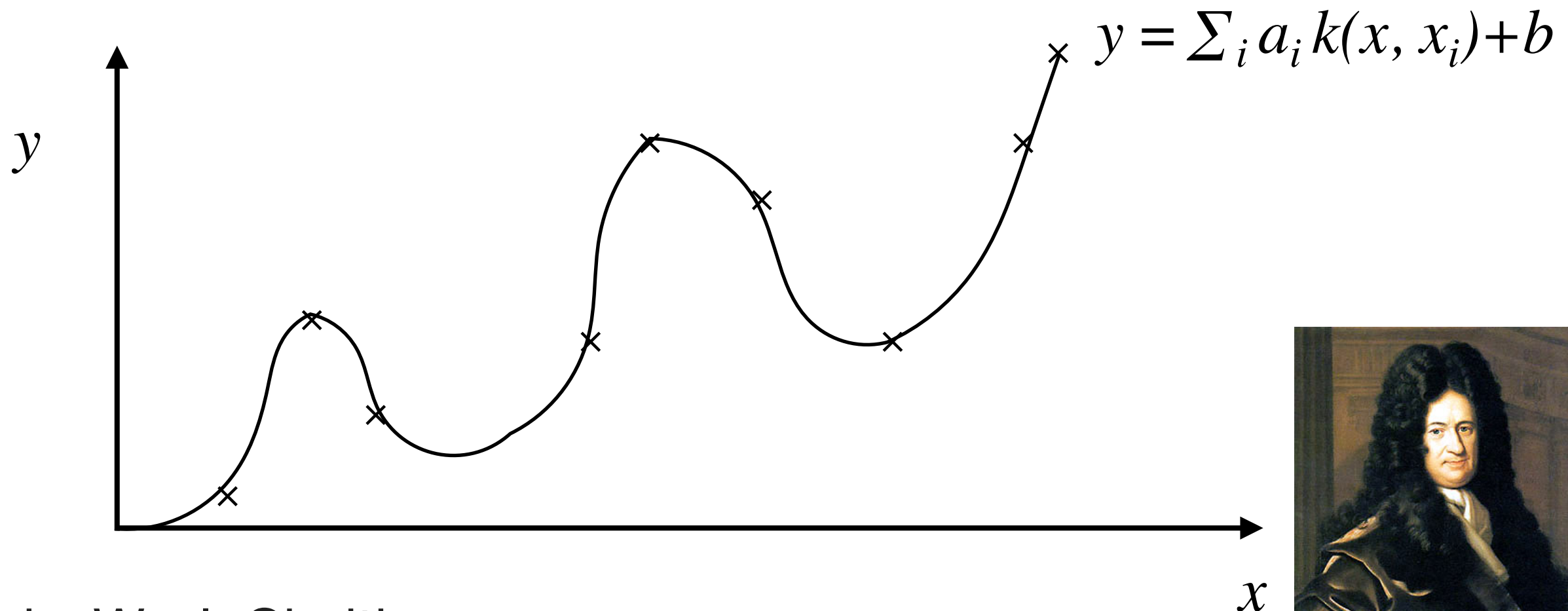


Leibniz, Weyl, Chaitin



Empirical Inference

- Drawing conclusions from empirical data (observations, measurements)
- Example 1: scientific inference

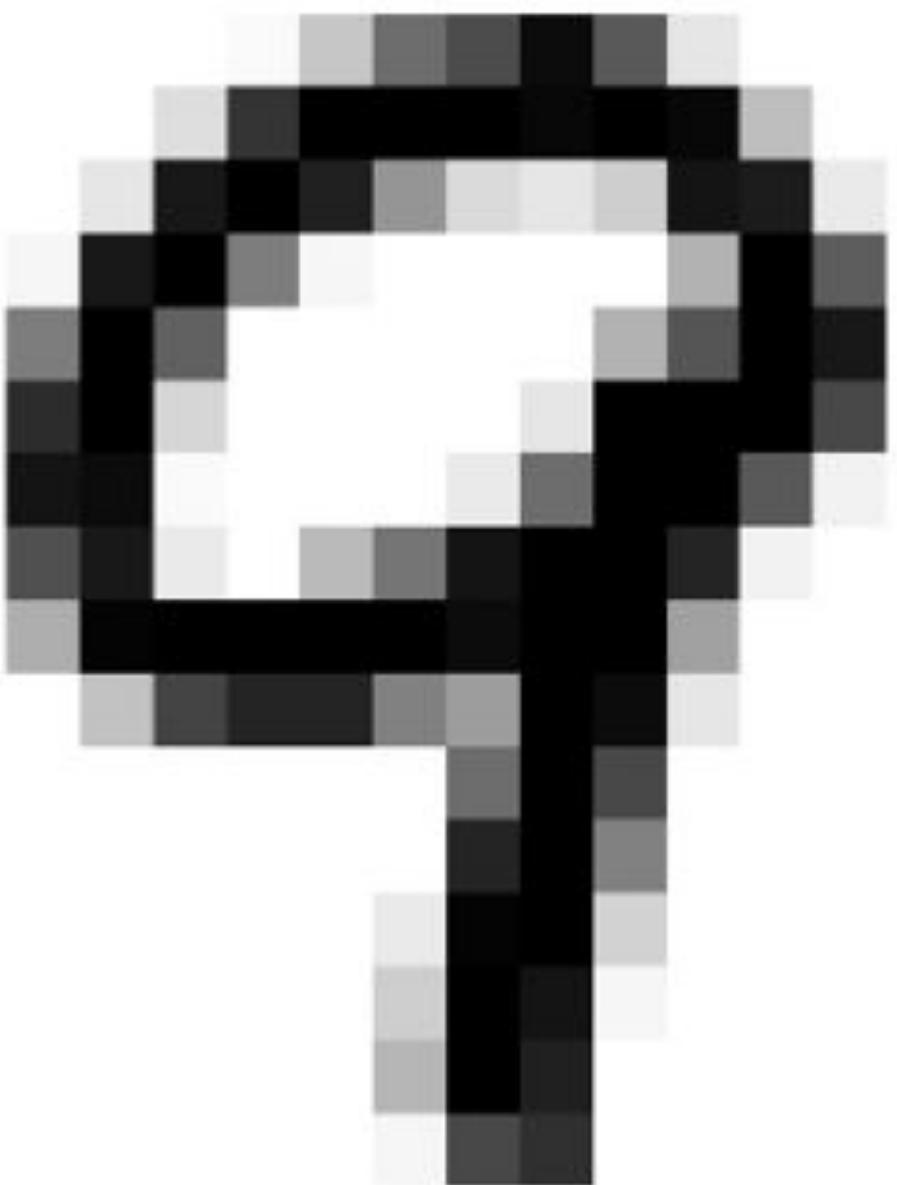


Leibniz, Weyl, Chaitin



Empirical Inference

- Example 2: perception



9



9



∞



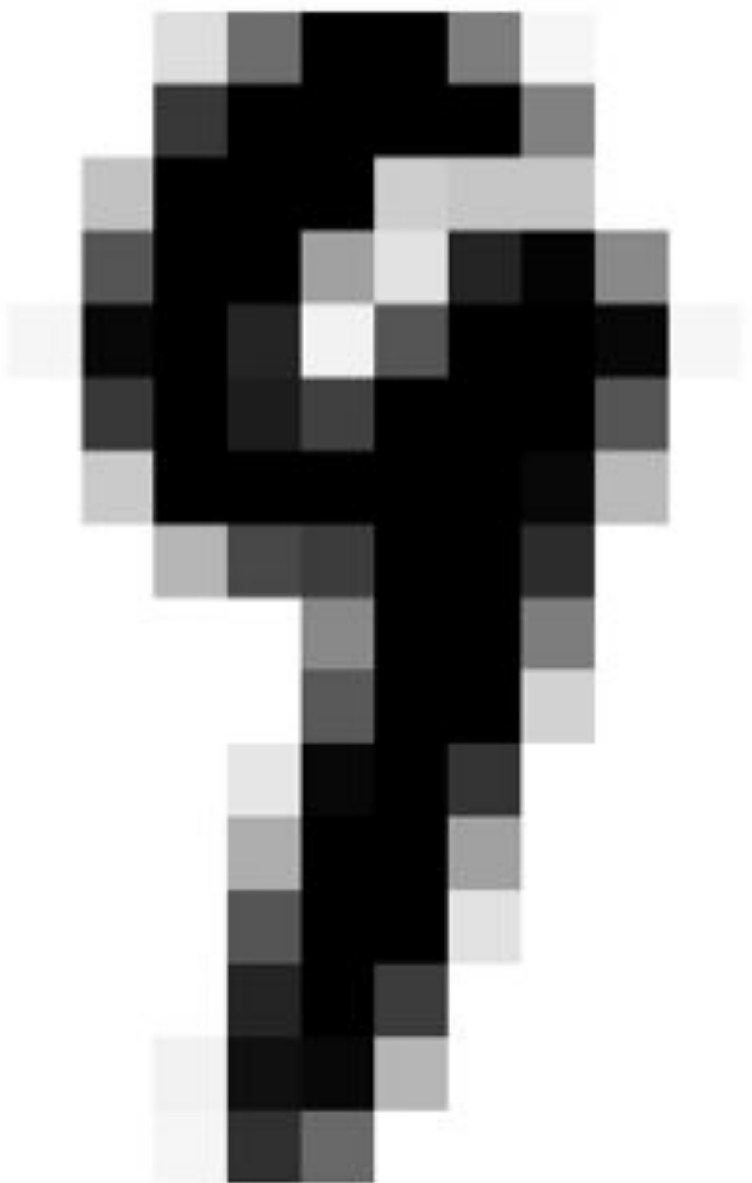
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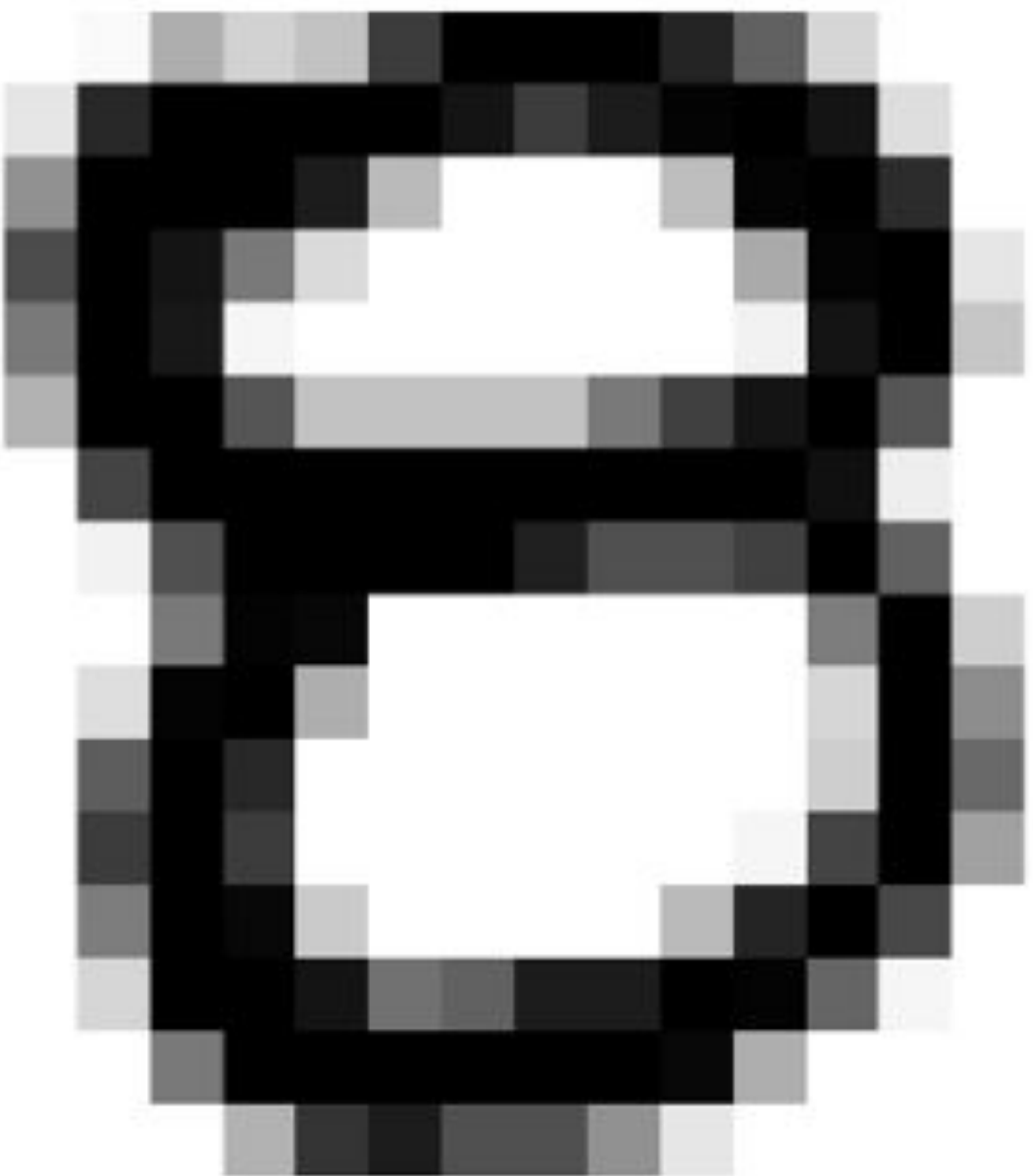
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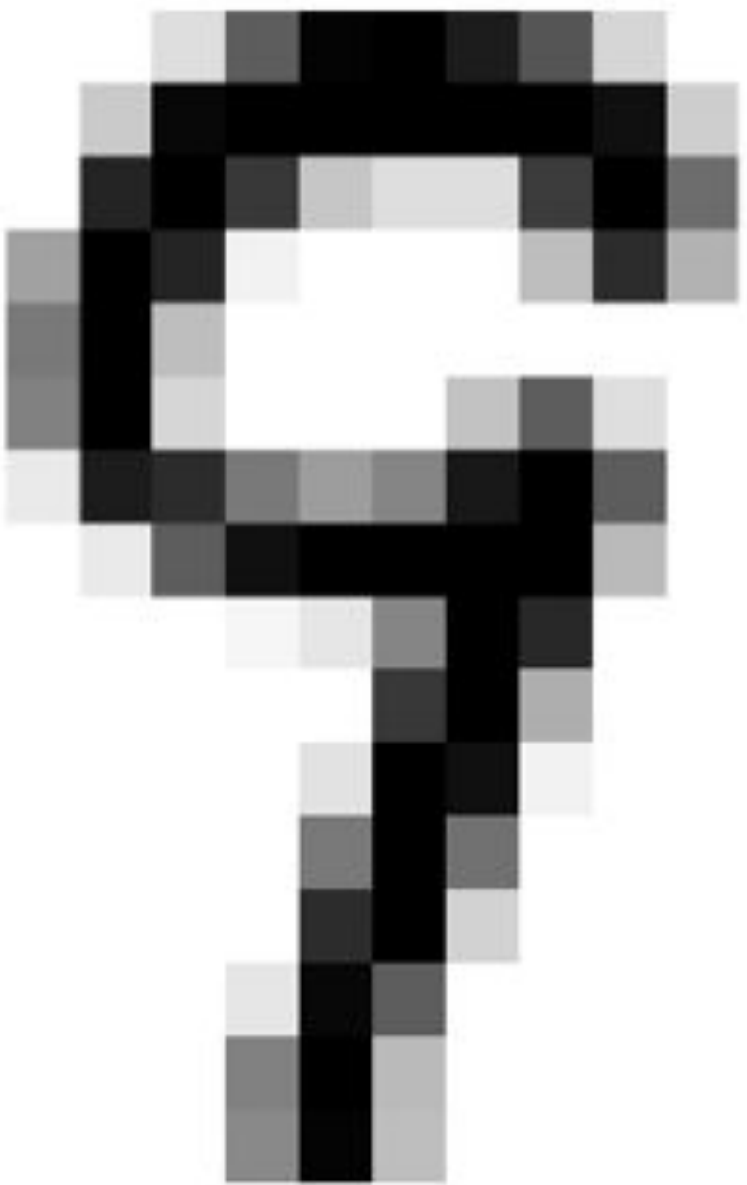
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9

Empirical Inference

- Example2: perception

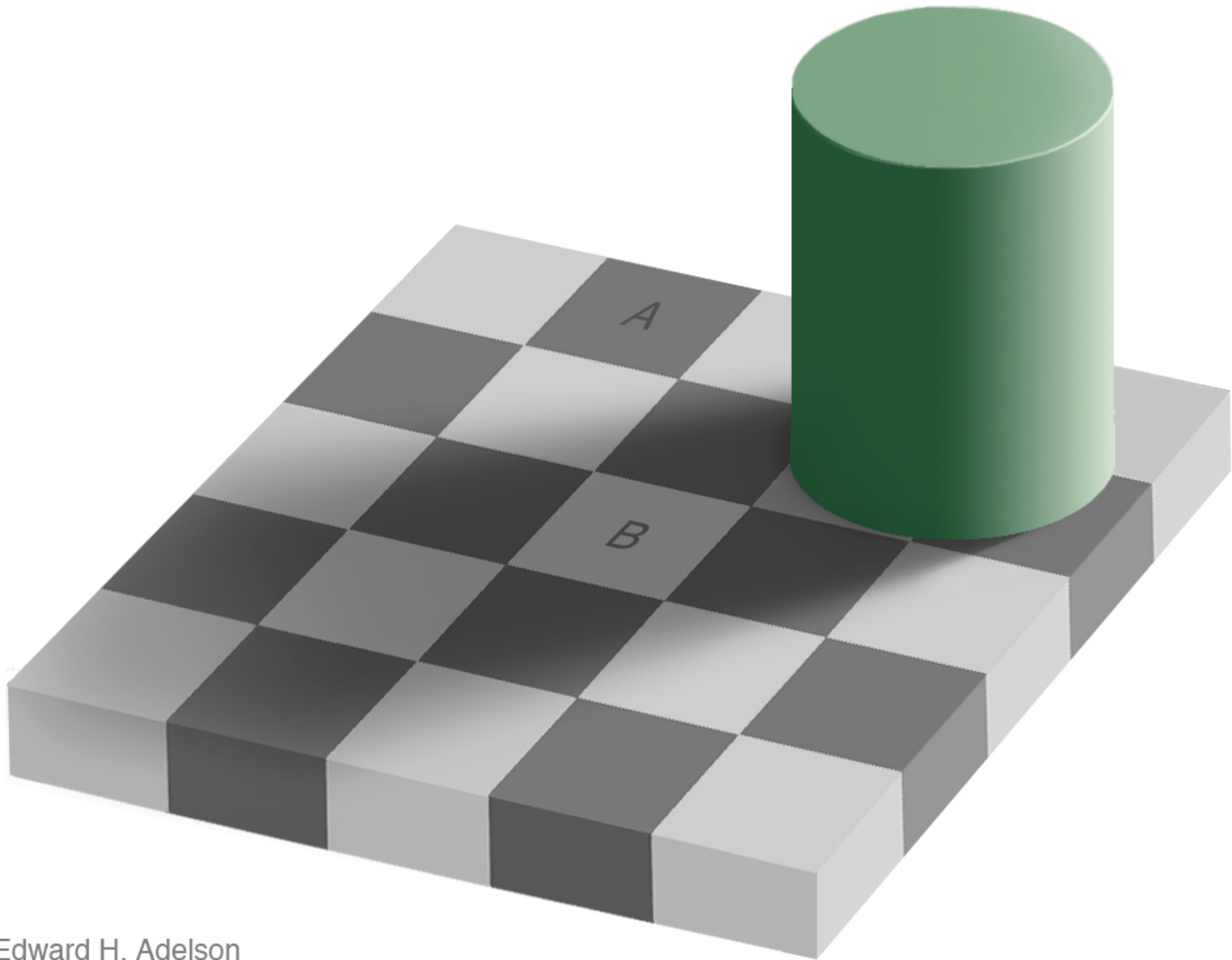
"The brain is nothing but a statistical decision organ"
H. Barlow

Color Perception

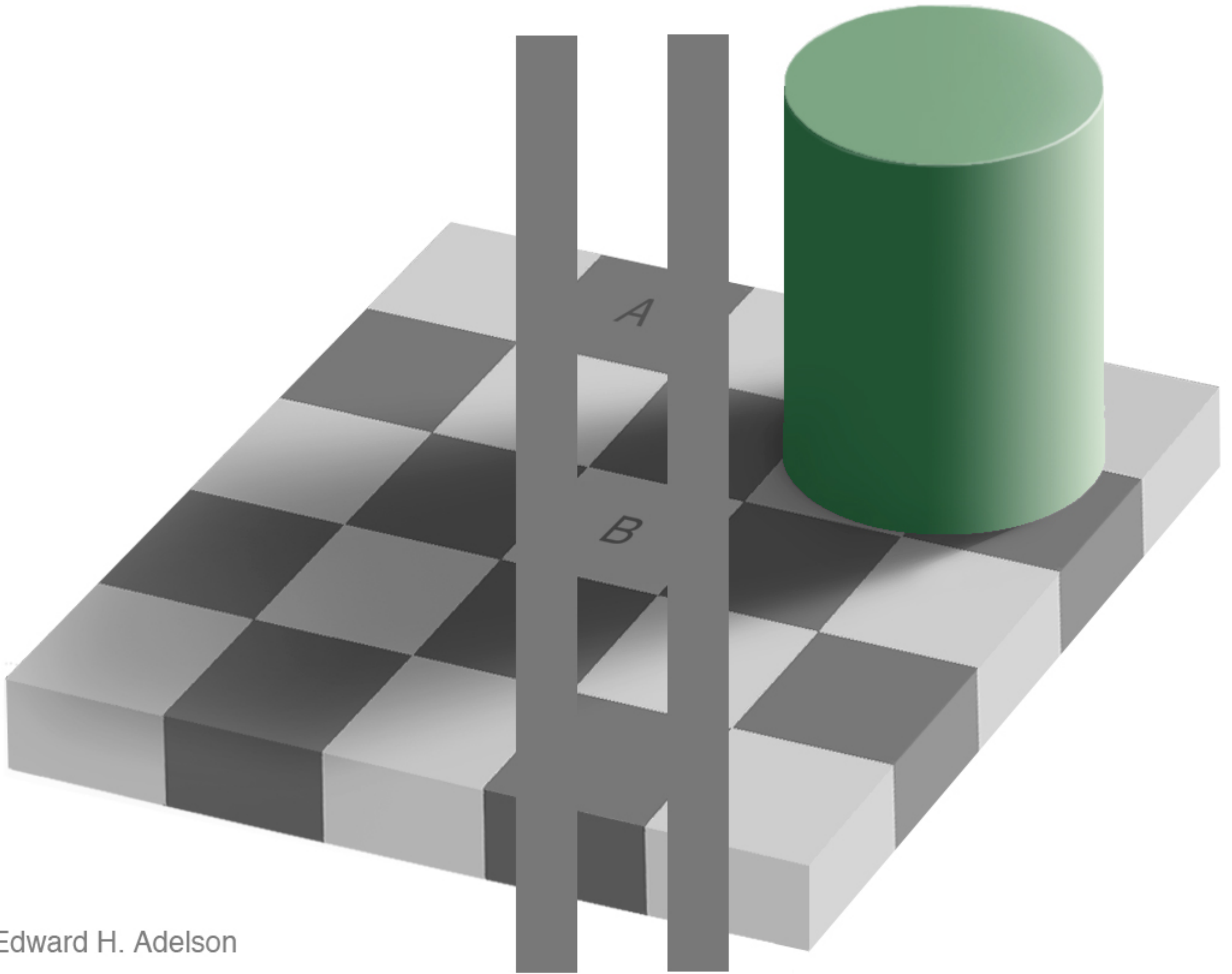


X

X



Edward H. Adelson



Edward H. Adelson

*reflected light = illumination * reflectance*

“Vision as unconscious inference”
Helmholtz

Hard Inference Problems

- High dimensionality — consider many factors simultaneously to find regularity
- Complex regularities — nonlinear; nonstationary, etc.
- Little prior knowledge — e.g. no mechanistic models for the data
- Need large data sets — processing requires computers and automatic inference methods

What is machine learning?

Example: Netflix Challenge

- Goal: Predict how a viewer will rate a movie
- 10% improvement = 1 million dollars



Example: Netflix Challenge

- Goal: Predict how a viewer will rate a movie
- 10% improvement = 1 million dollars
- Essence of Machine Learning:
 - A pattern exists
 - We cannot pin it down mathematically
 - We have data on it

AlphaGo vs Lee Sedol



NVIDIA BB8 AI Car

Mariusz Bojarski
NVIDIA Corporation
Holmdel, NJ 07735

Davide Del Testa
NVIDIA Corporation
Holmdel, NJ 07735

Daniel Dworakowski
NVIDIA Corporation
Holmdel, NJ 07735

Bernhard Firner
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Beat Flepp
NVIDIA Corporation
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Praseon Goyal
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Lawrence D. Jackel
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Mathew Monfort
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Urs Müller
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Jiakai Zhang
NVIDIA Corporation
Holmdel, NJ 07735

Xin Zhang
NVIDIA Corporation
Holmdel, NJ 07735

Jake Zhao
NVIDIA Corporation
Holmdel, NJ 07735

Karol Zieba
NVIDIA Corporation
Holmdel, NJ 07735

Abstract

We trained a convolutional neural network (CNN) to map raw pixels from a single front-facing camera directly to steering commands. This end-to-end approach proved surprisingly powerful. With minimum training data from humans the system learns to drive in traffic on local roads with or without lane markings and on highways. It also operates in areas with unclear visual guidance such as in parking lots and on unpaved roads.

The system automatically learns internal representations of the necessary processing steps such as detecting useful road features with only the human steering angle as the training signal. We never explicitly trained it to detect, for example, the outline of roads.

Compared to explicit decomposition of the problem, such as lane marking detection, path planning, and control, our end-to-end system optimizes all processing steps simultaneously. We argue that this will eventually lead to better performance and smaller systems. Better performance will result because the internal components self-optimize to maximize overall system performance, instead of optimizing human-selected intermediate criteria, e.g., lane detection. Such criteria understandably are selected for ease of human interpretation which doesn't automatically guarantee maximum system performance. Smaller networks are possible because the system learns to solve the problem with the minimal number of processing steps.

We used an NVIDIA DevBox and Torch 7 for training and an NVIDIA DRIVE™ PX self-driving car computer also running Torch 7 for determining where to drive. The system operates at 30 frames per second (FPS).



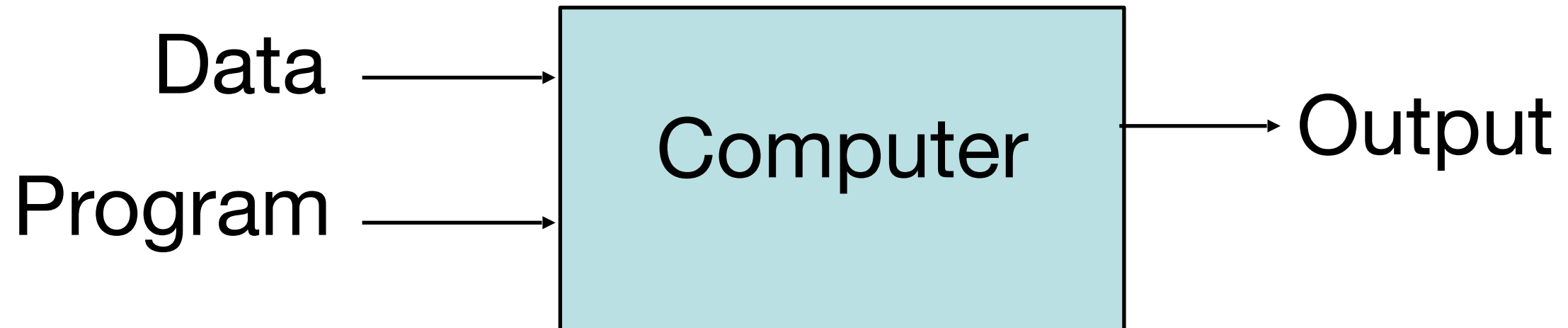
Meet NVIDIA BB8

What is Machine Learning?

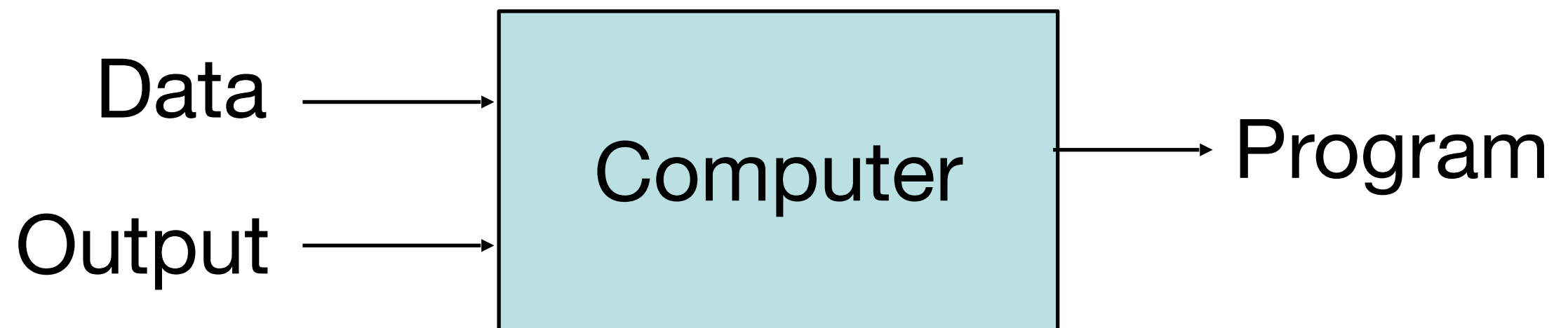
- [Arthur Samuel, 1959]
 - Field of study that gives computers the ability to learn without being explicitly programmed
- [Kevin Murphy] algorithms that
 - automatically detect patterns in data
 - use the uncovered patterns to predict future data or other outcomes of interest
- [Tom Mitchell] algorithms that
 - improve their performance (P) at some task (T) with experience (E)

Comparison

- **Traditional Programming**

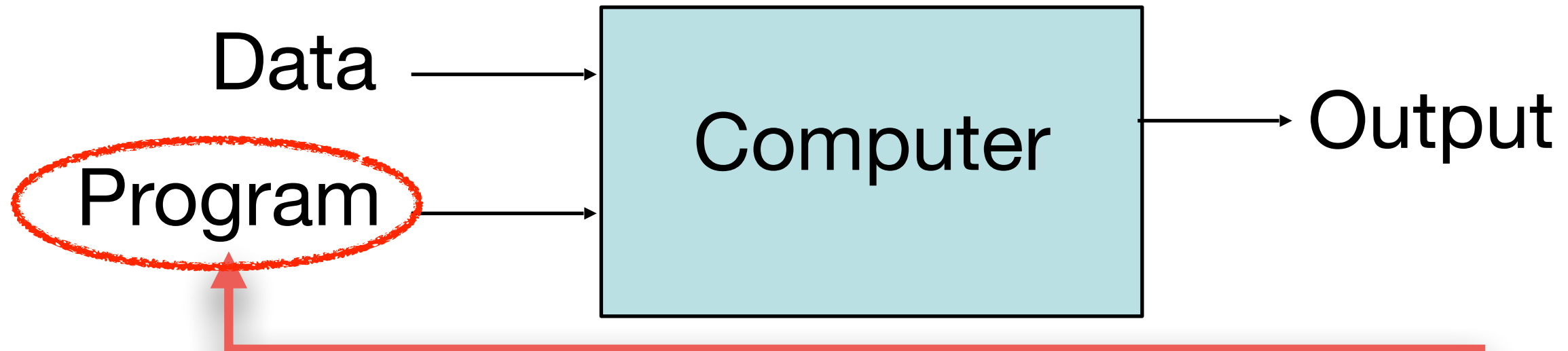


- **Machine Learning**

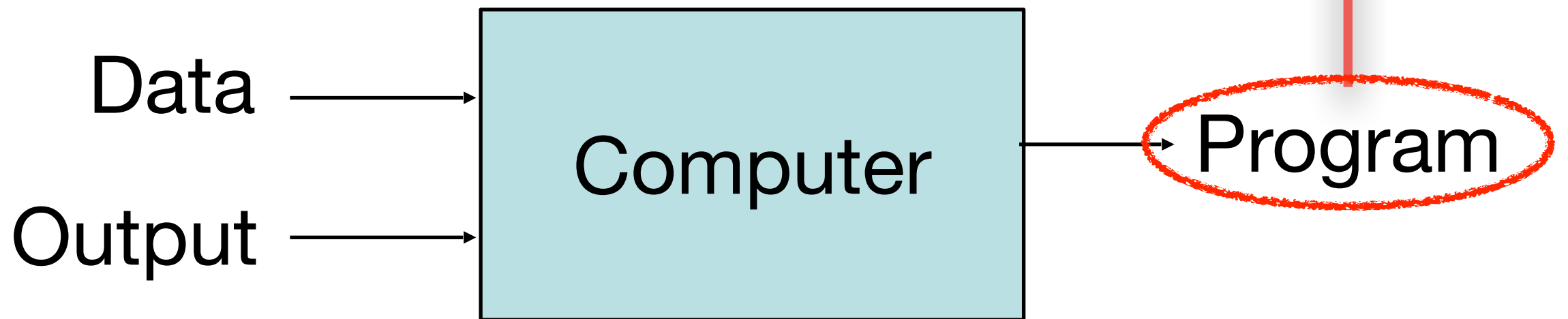


Comparison

- **Traditional Programming**



- **Machine Learning**



What is Machine Learning?

- If you are a Scientist



- If you are an Engineer / Entrepreneur
 - Get lots of data
 - Machine Learning
 - ???
 - Profit!

Why Study Machine Learning?

Engineering Better Computing Systems

- Develop systems
 - too difficult/expensive to construct manually
 - because they require specific detailed skills/knowledge
 - **knowledge engineering bottleneck**
- Develop systems
 - that adapt and customize themselves to individual users.
 - Personalized news or mail filter
 - Personalized tutoring
- Discover new knowledge from large databases
 - Medical text mining (e.g. migraines to calcium channel blockers to magnesium)
 - **data mining**

Why Study Machine Learning?

Cognitive Science

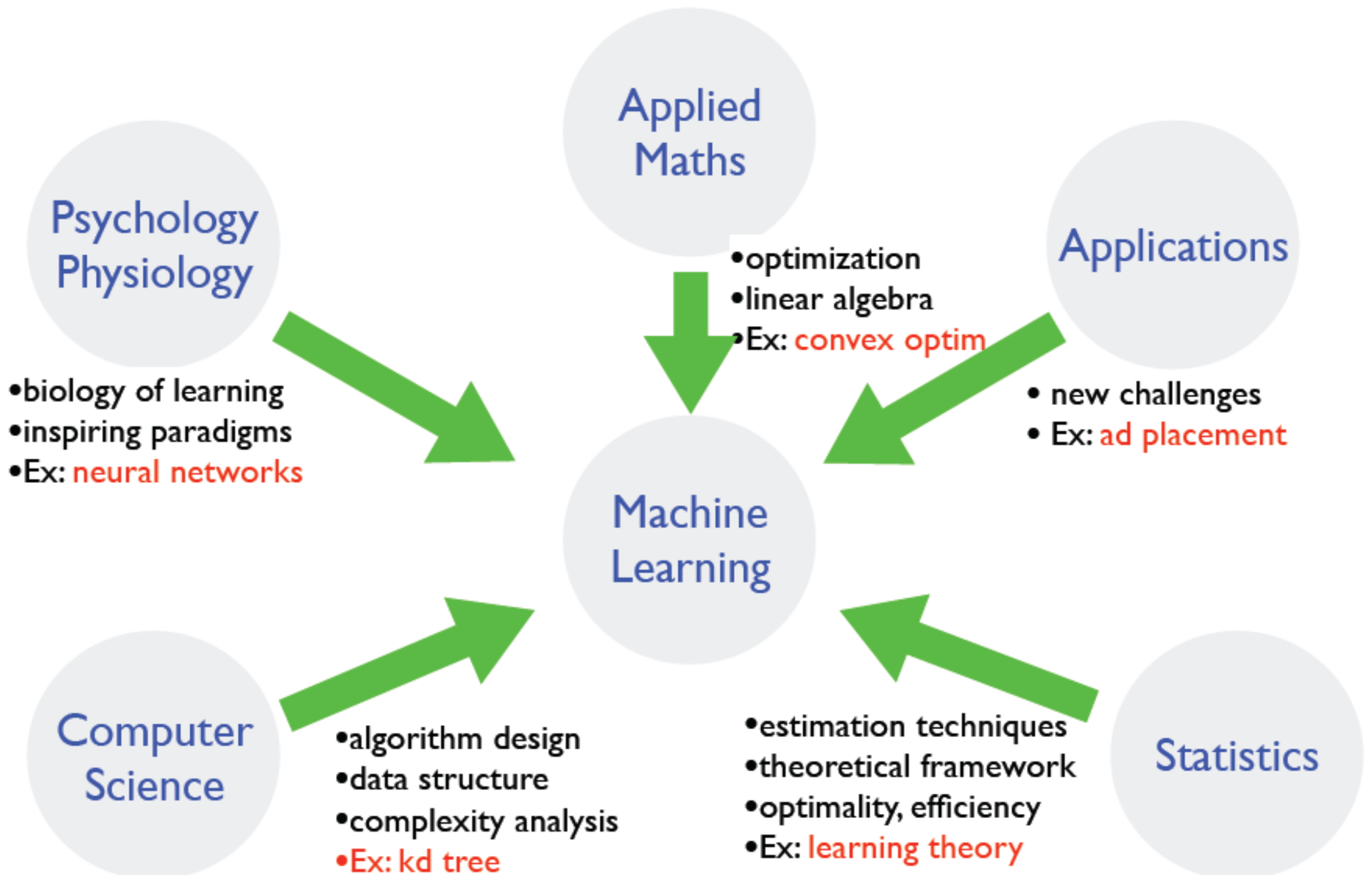
- Computational studies of learning may help us understand learning in humans
 - and other biological organisms.
- Hebbian neural learning
 - “Neurons that fire together, wire together.”

Why Study Machine Learning?

The Time is Ripe

- Algorithms
 - Many basic effective and efficient algorithms available.
- Data
 - Large amounts of on-line data available.
- Computing
 - Large amounts of computational resources available.

Where does ML fit in?



A Brief History of AI



A Proposal for the Dartmouth Summer Research Project on Artificial Intelligence.

(John McCarthy)



1956

A Proposal for the

DARTMOUTH SUMMER RESEARCH PROJECT ON ARTIFICIAL INTELLIGENCE

June 17 - Aug. 16

We propose that a 2 month, 10 man study of artificial intelligence be carried out during the summer of 1956 at Dartmouth College in Hanover, New Hampshire. The study is to proceed on the basis of the conjecture that every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it. An attempt will be made to find how to make machines use language, form abstractions and concepts, solve kinds of problems now reserved for humans, and improve themselves. We think that a significant advance can be made in one or more of these problems if a carefully selected group of scientists work on it together for a summer.

The following are some aspects of the artificial intelligence problem:

1) Automatic Computers

If a machine can do a job, then an automatic calculator can be programmed to simulate the machine. The speeds and memory capacities of present computers may be insufficient to simulate many of the higher functions of the human brain, but the major obstacle is not lack of machine capacity, but our inability to write programs taking full advantage of what we have.

2) How Can a Computer be Programmed to Use a Language

It may be speculated that a large part of human thought consists of manipulating words according to rules of reasoning

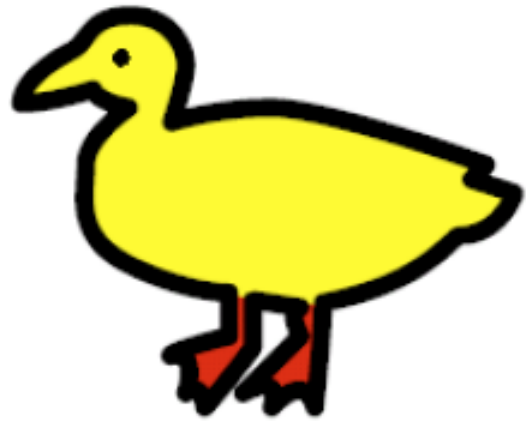


Why is AI hard?

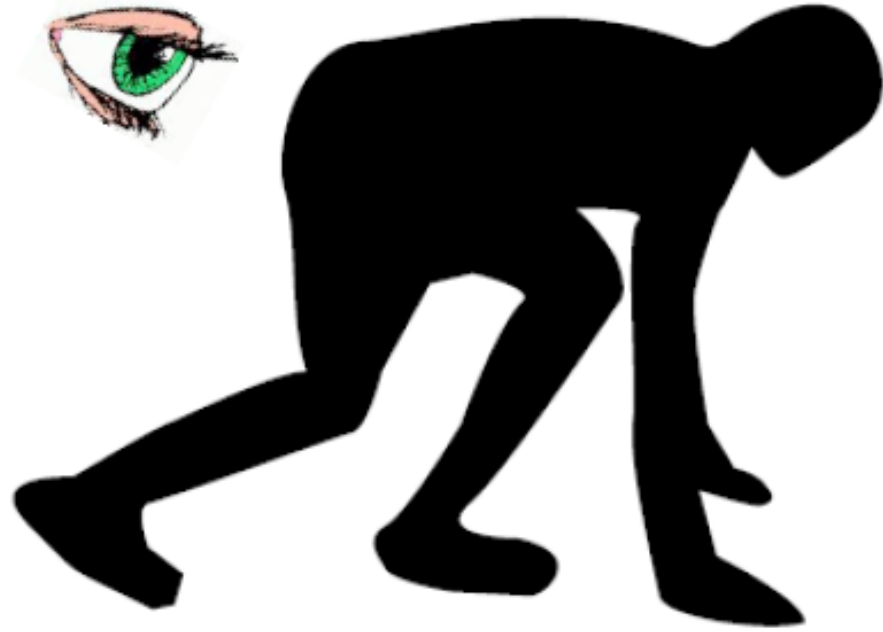
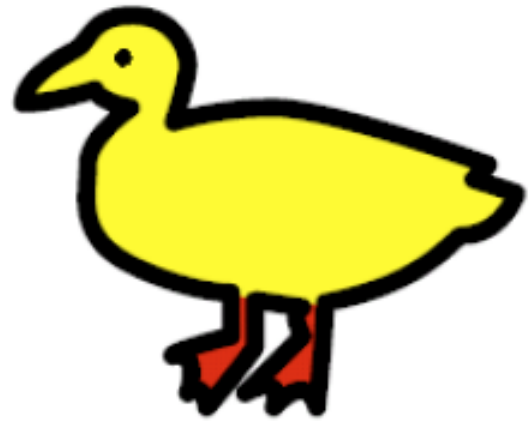
Image credit: Neşeli Günler (Arzu Film, 1978)



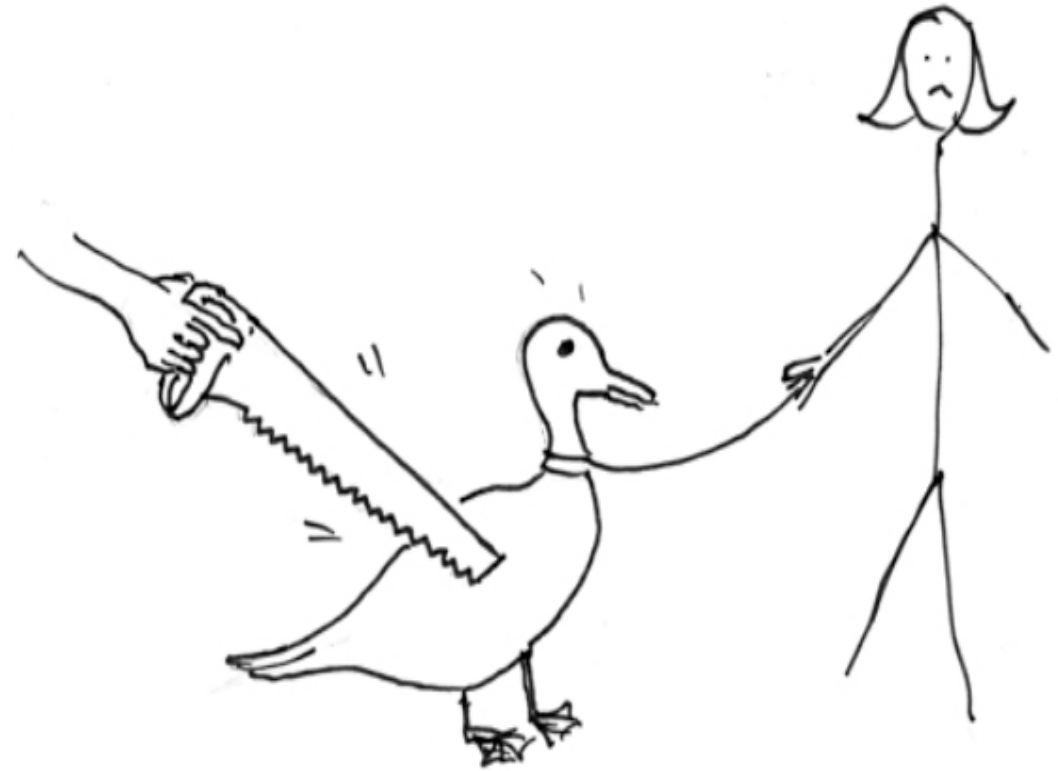
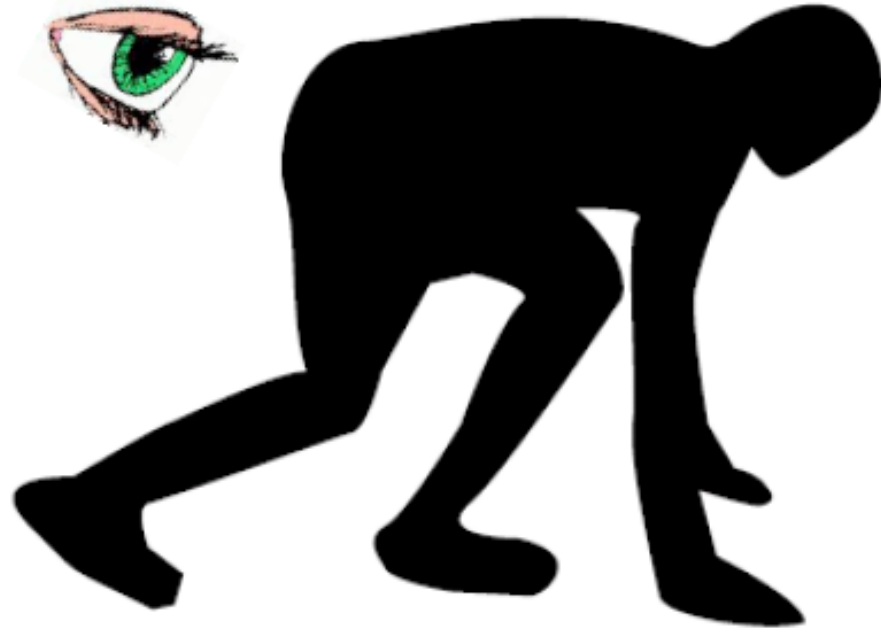
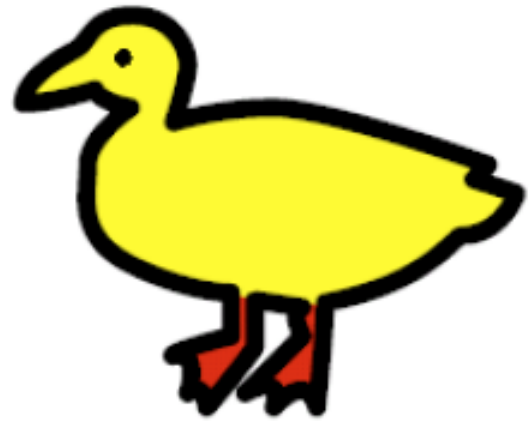
“I saw her duck”



“I saw her duck”



“I saw her duck”



Why are things working today?

- More compute power
- More data
- Better algorithms/models

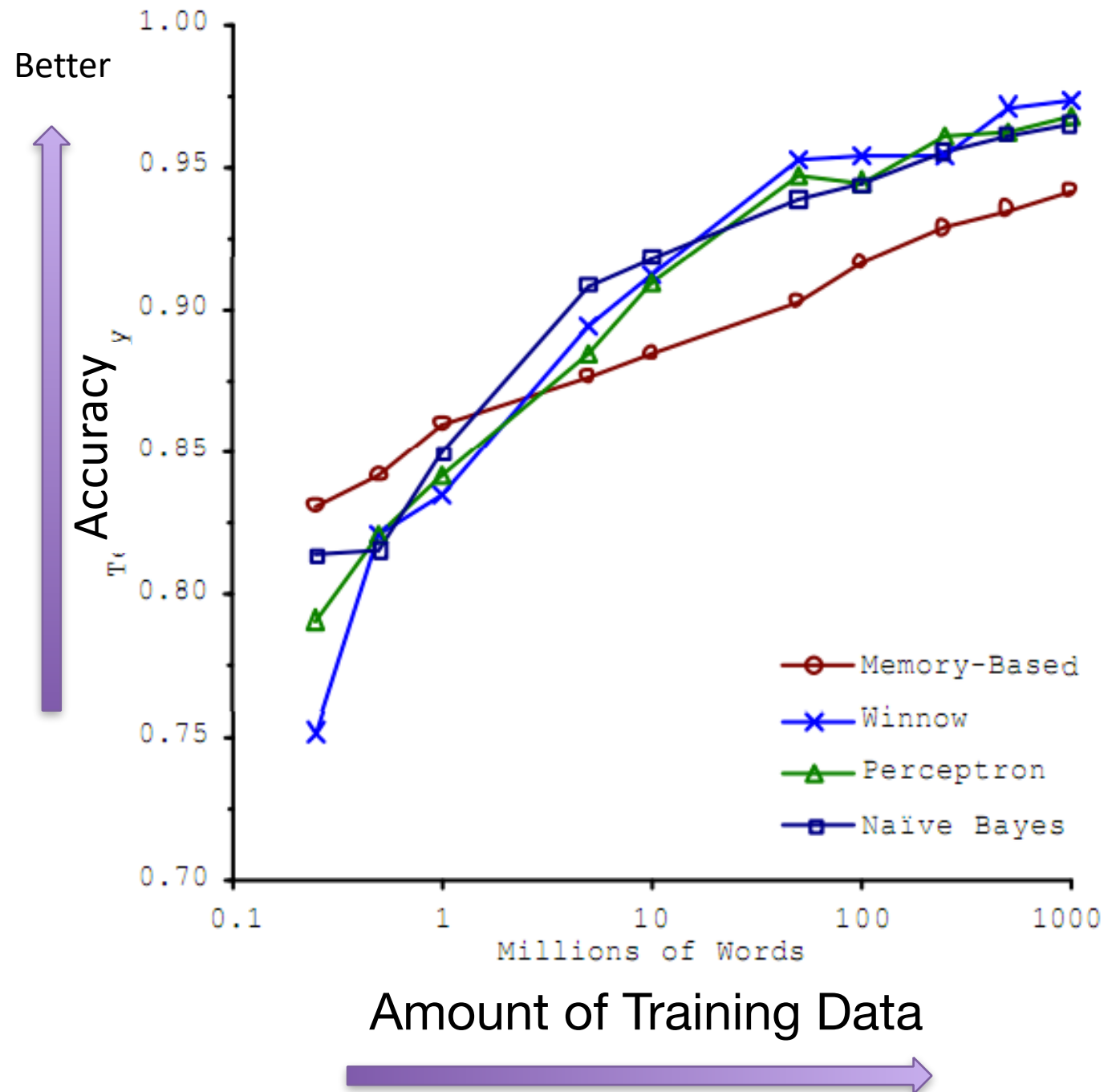


Figure Credit: Banko & Brill, 2011

Next Class:

Machine Learning by Examples,
Nearest Neighbor Classifier