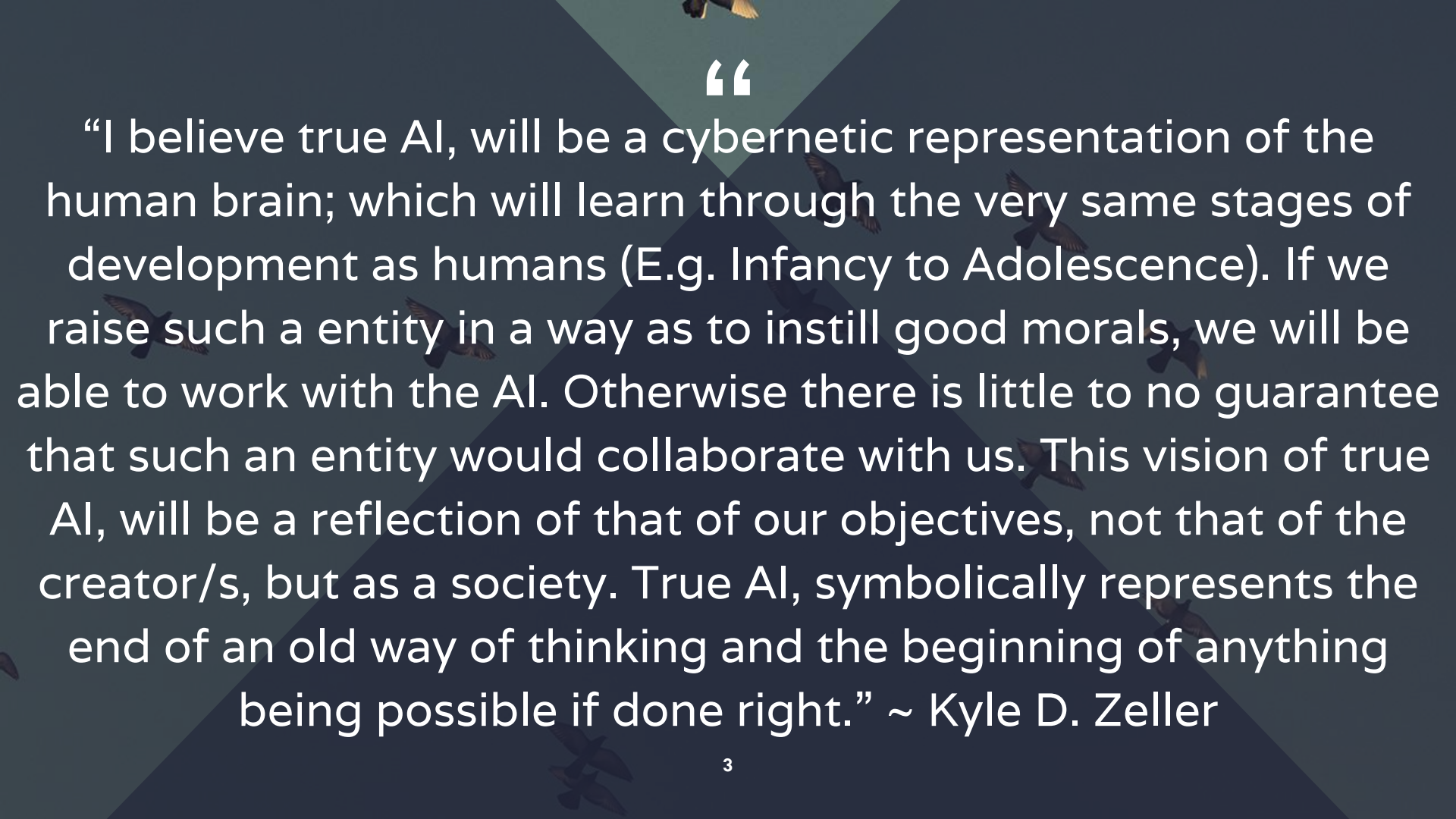
Machine Learning Crash Course

WEEK 9

“

“I believe this artificial intelligence is going to be our partner. If we misuse it, it will be a risk. If we use it right, it can be our partner.” ~ Masayoshi Son



“I believe true AI, will be a cybernetic representation of the human brain; which will learn through the very same stages of development as humans (E.g. Infancy to Adolescence). If we raise such a entity in a way as to instill good morals, we will be able to work with the AI. Otherwise there is little to no guarantee that such an entity would collaborate with us. This vision of true AI, will be a reflection of that of our objectives, not that of the creator/s, but as a society. True AI, symbolically represents the end of an old way of thinking and the beginning of anything being possible if done right.” ~ Kyle D. Zeller

Topics

- Anomaly Detection
  - Density Estimation
  - System Design
- Recommender Systems
  - Problem Formation
  - Content Recommendations
  - Potential Issues
  - Alternate Parameter Learning Choices
- Large Scale Machine Learning
  - ML with Large Data Sets
  - Stochastic Gradient Descent
  - Mini-Batch Gradient Descent
  - Online Learning
  - Map Reduce & Data Parallelism

1. Anomaly Detection

Introduction

- What is it?
- What do we use it for?
- What ways can we represent these types of problems?

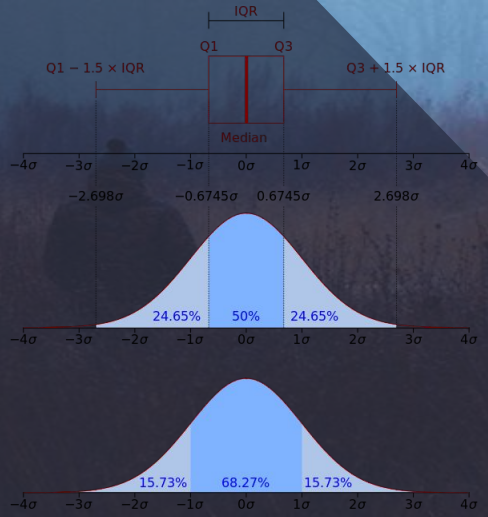
$$\hat{f} = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{x - x_i}{h}\right) \qquad K(x) = \frac{1}{\sqrt{2\pi}} e^{-x^2/2}$$

Density Estimation or Kernel Density Estimation (KDE)

DEMO

What is it?
"A non-parametric way to estimate the **probability density function** of a random variable."~Wiki

Probability Density Function:
A modeling of the likelihood/probability that the value of some arbitrary random variable equals a particular sample.



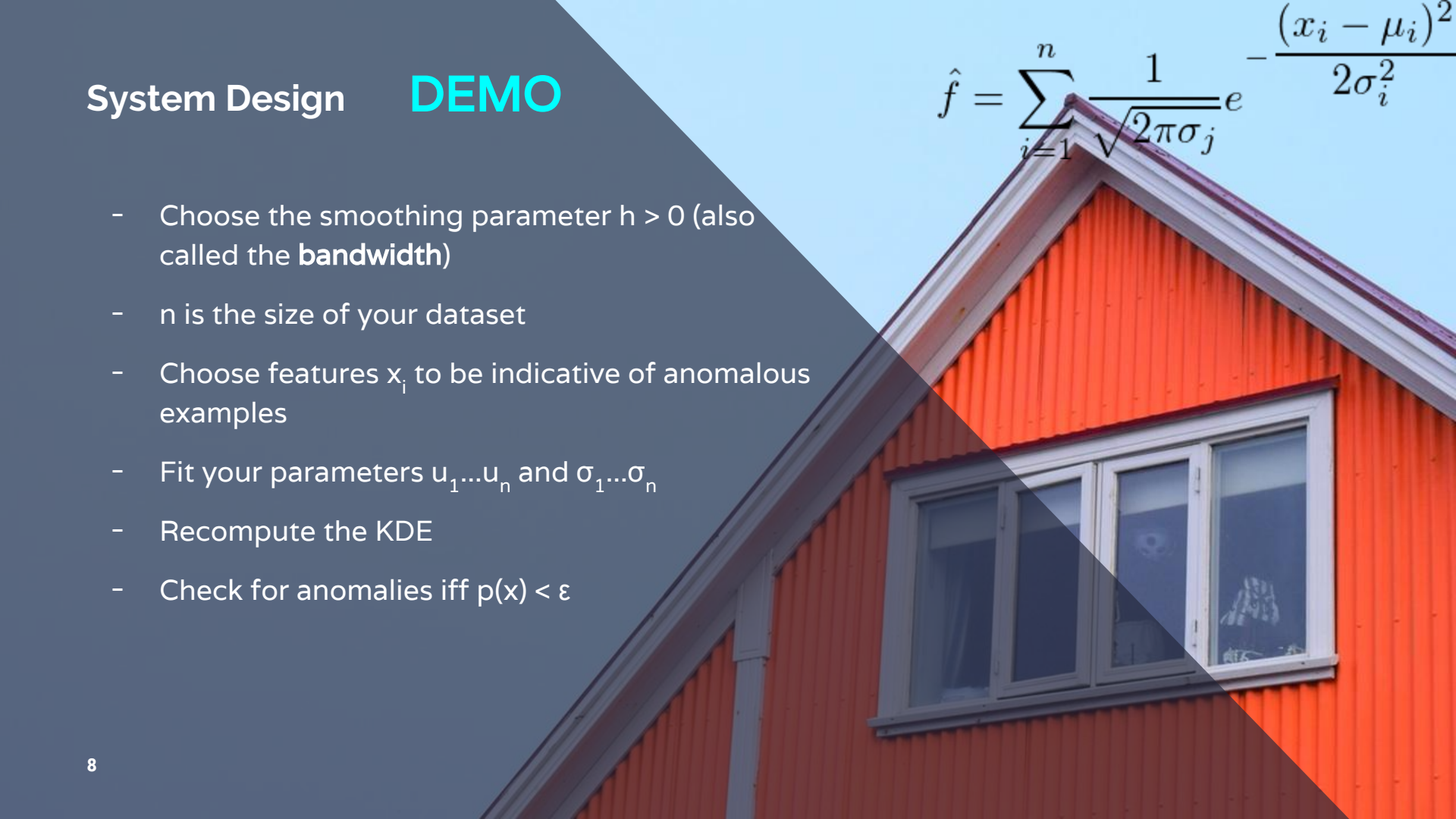
Smoothing Function K
This is used to capture important features in the data, while leaving out noisy artifacts.

Our Choice of K:
We will consider a gaussian smoothing function for our KDE.

System Design DEMO

$$\hat{f} = \sum_{i=1}^{n} \frac{1}{\sqrt{2\pi\sigma_j}} e^{-\frac{(x_i - \mu_i)^2}{2\sigma_i^2}}$$

- Choose the smoothing parameter h > 0 (also called the **bandwidth**)
- n is the size of your dataset
- Choose features x_i to be indicative of anomalous examples
- Fit your parameters $u_1 \ldots u_n$ and $\sigma_1 \ldots \sigma_n$
- Recompute the KDE
- Check for anomalies iff $p(x) < \varepsilon$



2. Recommender Systems

Introduction

- What is it?
- What do we use it for?
- What ways can we represent these types of problems?

Problem Formation

- Consider Movie Ratings (Trivial Case)
  - n users / m movies / [1-5] ratings
  - Based purely on the rating of the movie you could show the user similar rated movies

Content Recommendations

DEMO

- Given the example of movies
- Consider category based scoring (e.g. action, comedy, and/or romance), as well as the ratings
- Develop a parameter to learn the preference, based on how a user rated the movie and categorized it

Potential Issues

- Mislabeled content
- Deliberate alterations ratings or categorization
- No labeling of content

Alternate Parameter Learning Choices

DEMO

- Clustering Approach
  - KMeans
  - FuzzyCMeans
- Neural Networks
  - MLP

3. Large Scale Machine Learning

ML with Large Data Sets

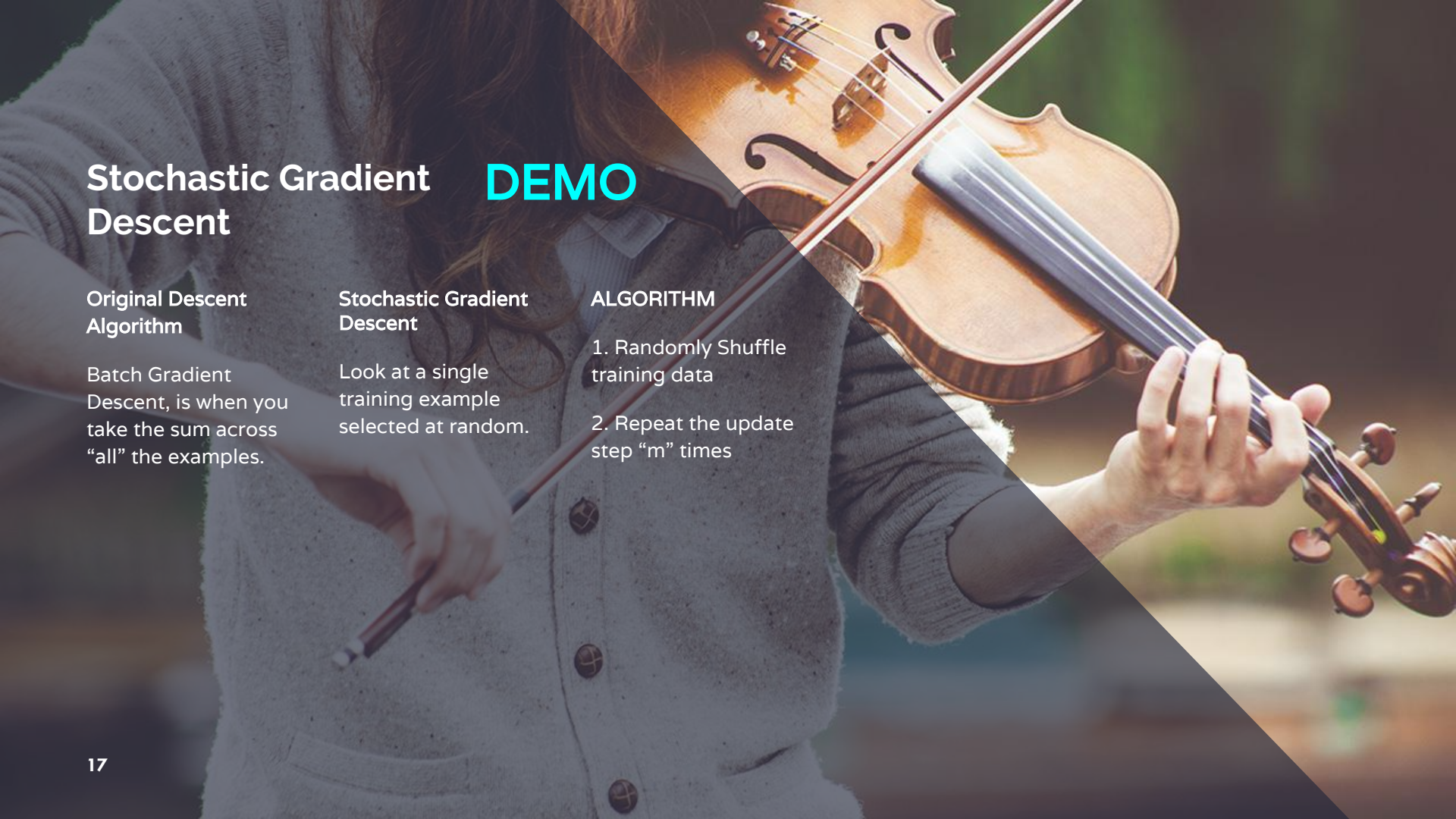
Issues

- Computational issues e.g. one step of gradient descent over 100 million data points

Data Intuition

More data will triumph over a better algorithm.

DEMO



Stochastic Gradient Descent

DEMO

Original Descent Algorithm

Batch Gradient Descent, is when you take the sum across “all” the examples.

Stochastic Gradient Descent

Look at a single training example selected at random.

ALGORITHM

1. Randomly Shuffle training data

2. Repeat the update step “m” times

Mini-Batch Gradient Descent

DEMO

Use b examples in each iteration.

It is fairly common to randomly select batches of data.

It can outperform stochastic gradient descent in a vectorized implementation.

ALGORITHM

1. Randomly select batches of b length

2. Repeat the update step (mb) times

Online Learning

DEMO

What is it?

A circumstance, when we want to learn from a continuous stream of information.

When can we use it?

A large quantity of live data and/or users.

Examples

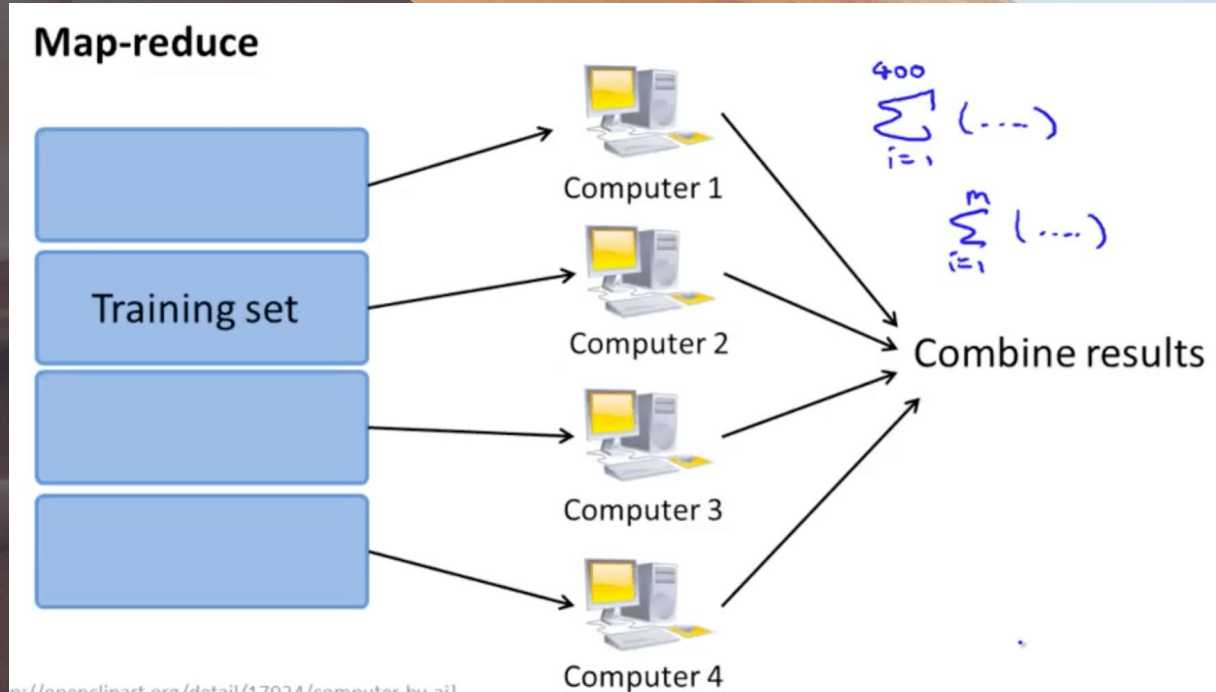
Online shopping websites, ad monitoring

Map Reduce and Data Parallelism

DEMO

Examples

- Multi-Threading
- Cluster Computing
- Running code on the GPU




CODE

THANKS!

Any questions?

You can find me on:

- LInkedin
- GitHub
  - ECE-Engineer
- Gmail
  - kzeller@oswego.edu
- Twitter

CREDITS

- https://en.wikipedia.org/wiki/Probability_density_function
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- https://chemicalstatistician.wordpress.com/2013/06/09/exploratory-data-analysis-kernel-density-estimation-in-r-on-ozone-pollution-data-in-new-york-and-ozonopolis/
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