Summary

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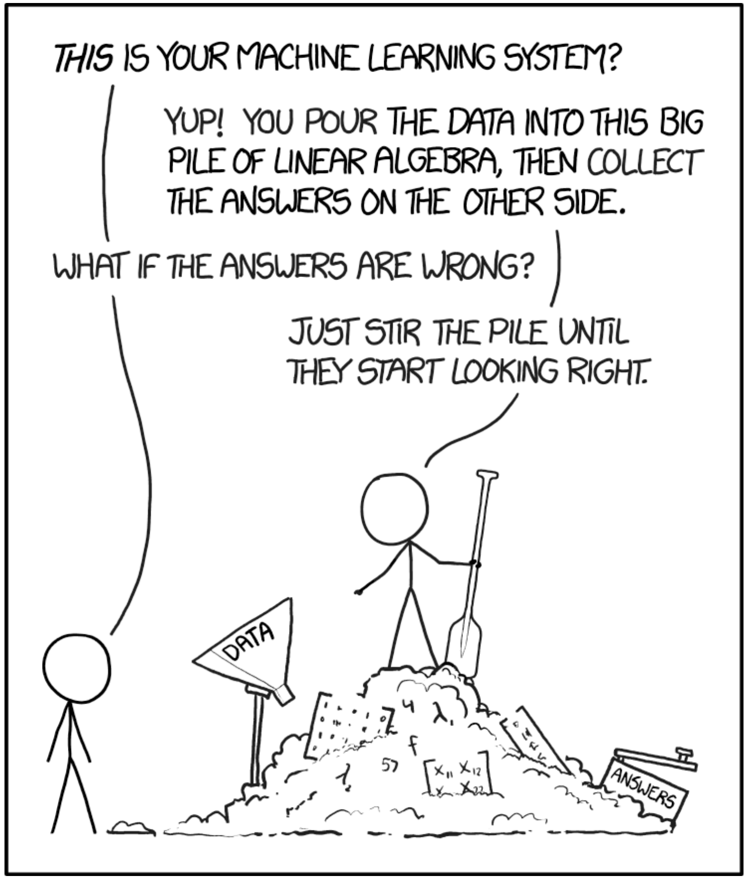
IC-CVLab

EPFL

What is Machine Learning?

Machine learning algorithms:

- seek to provide knowledge to computers through data, observations, and interaction with the world,
- can make predictions given new observations,
- improve when given access to large amounts of training data.



https://xkcd.com/

Artificial Intelligence

Artificial Intelligence

Expert Systems *A**

min-max

Machine Learning

Support Vector Machines

Boosting *Random Forests*

Deep Learning

Lenet *VGG*

ResNet

1997: Deep blue beats chess world champion

2017: AlphaGo beats go world champion

Self-Driving Cars

1985

DARPA ALV

2007

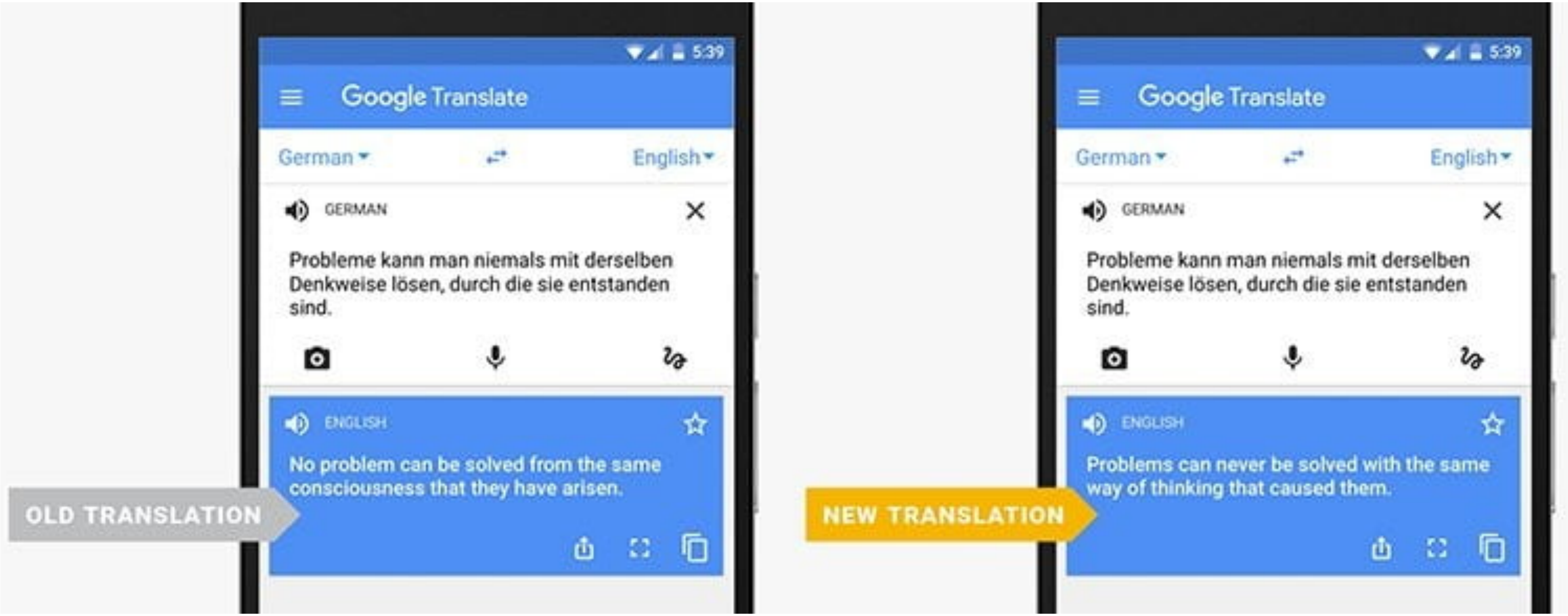
DARPA Urban Challenge

2016
2024

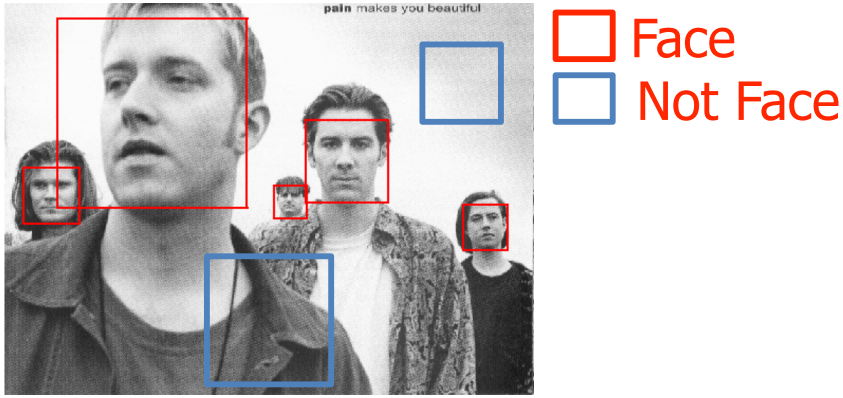
Google Cars
Uber
Waymo

- More computing power.
- Better sensors.
- Detailed maps of the environment.
- Machine learning

Machine Translation

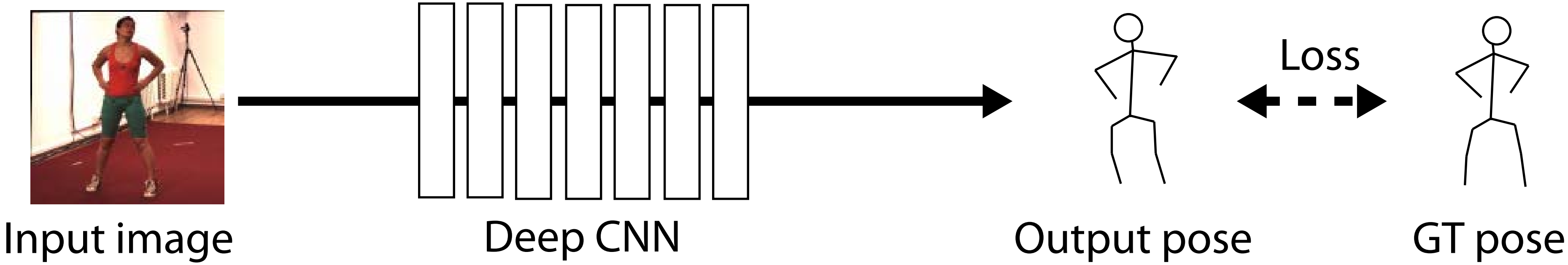


Classification vs Regression



Spam or not

- Classification algorithms seek to estimate a mapping function y from the input vector **x** to discrete or categorical output variables.



- Regression algorithms seek to estimate the mapping function y from the input vector **x** to **numerical or continuous** output variables.

Supervised Classification

Predicted label for sample n

Minimize:

$$E(\mathbf{w}) = \sum_{n=1}^{N} L(y(\mathbf{x}_n; \mathbf{w}), t_n)$$

True label for sample n

- **x:** Feature vector
- **w:**Model parameters
- t: Label
- y: Predictor
- L: Loss Function
- E: Error Function

—> ML is an optimization problem

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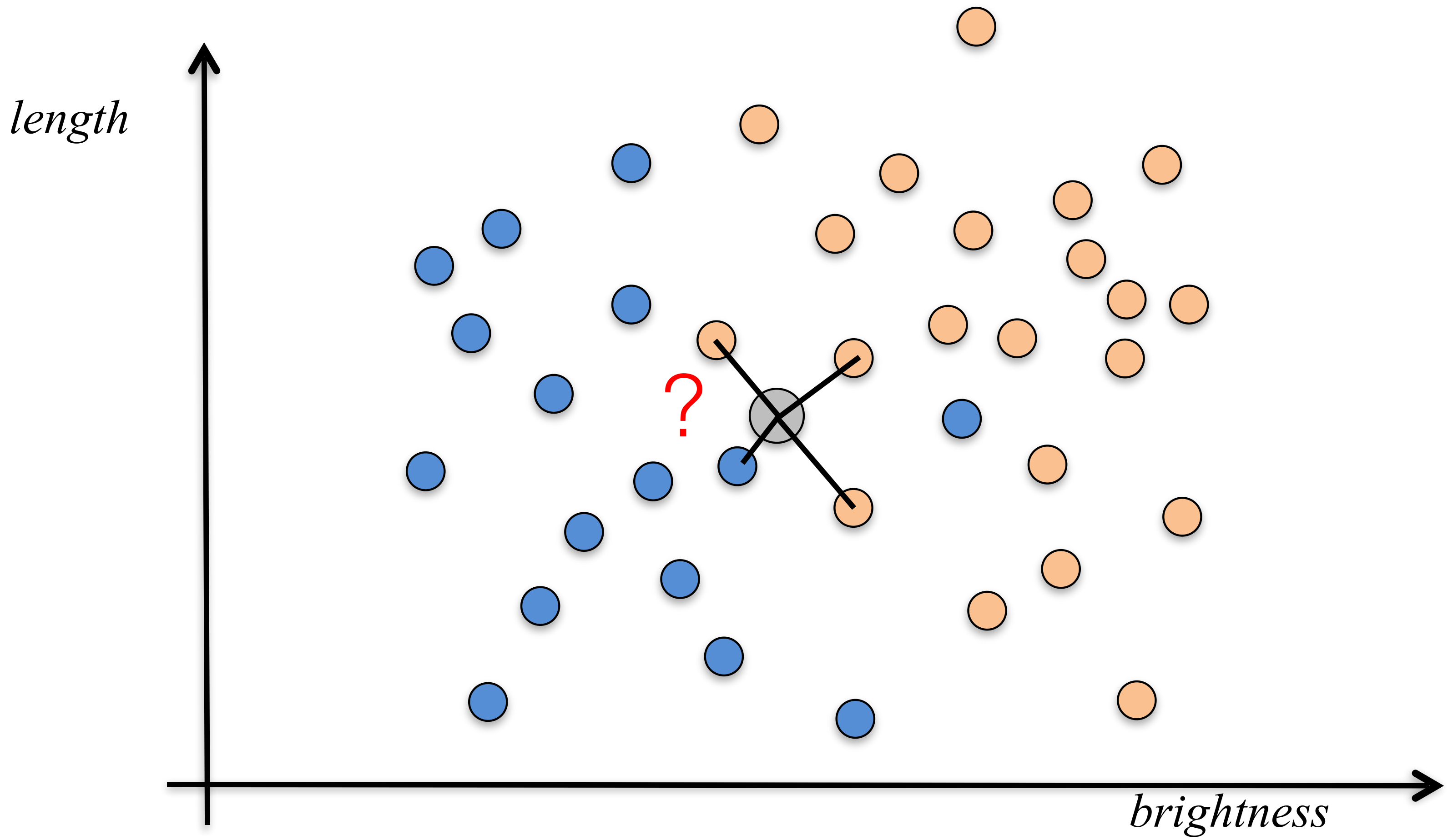
Classification Techniques

- Nearest-Neighbors and K-Means
- Logistic Regression
- Boosting
- Support Vector Machines
- Decision Trees and Forests
- Multilayer Perceptrons
- Convolutional Neural Networks
- Tranformers

K-Nearest-Neighbor Classifier

Improved algorithm:

- Given a new **x** to be classified, find its k nearest neighbors in the training set.
- Classify the point according to the majority of labels of its nearest neighbors.



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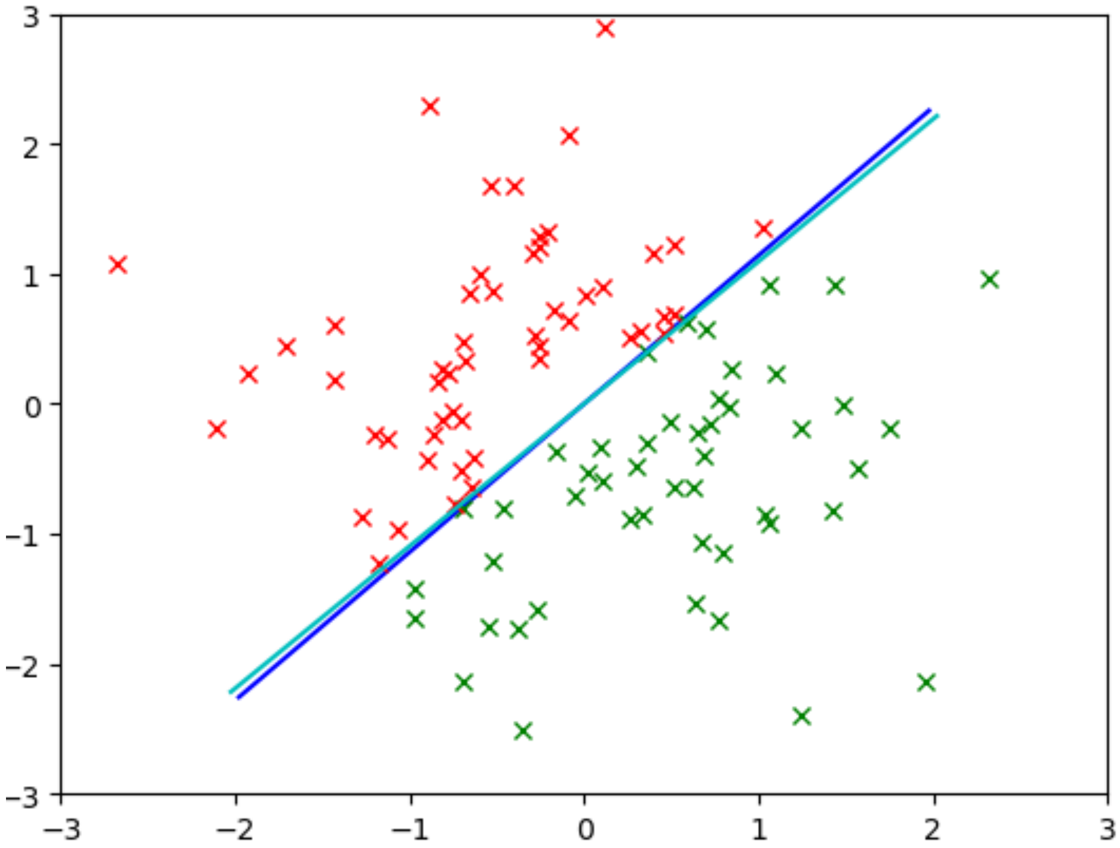
Perceptron

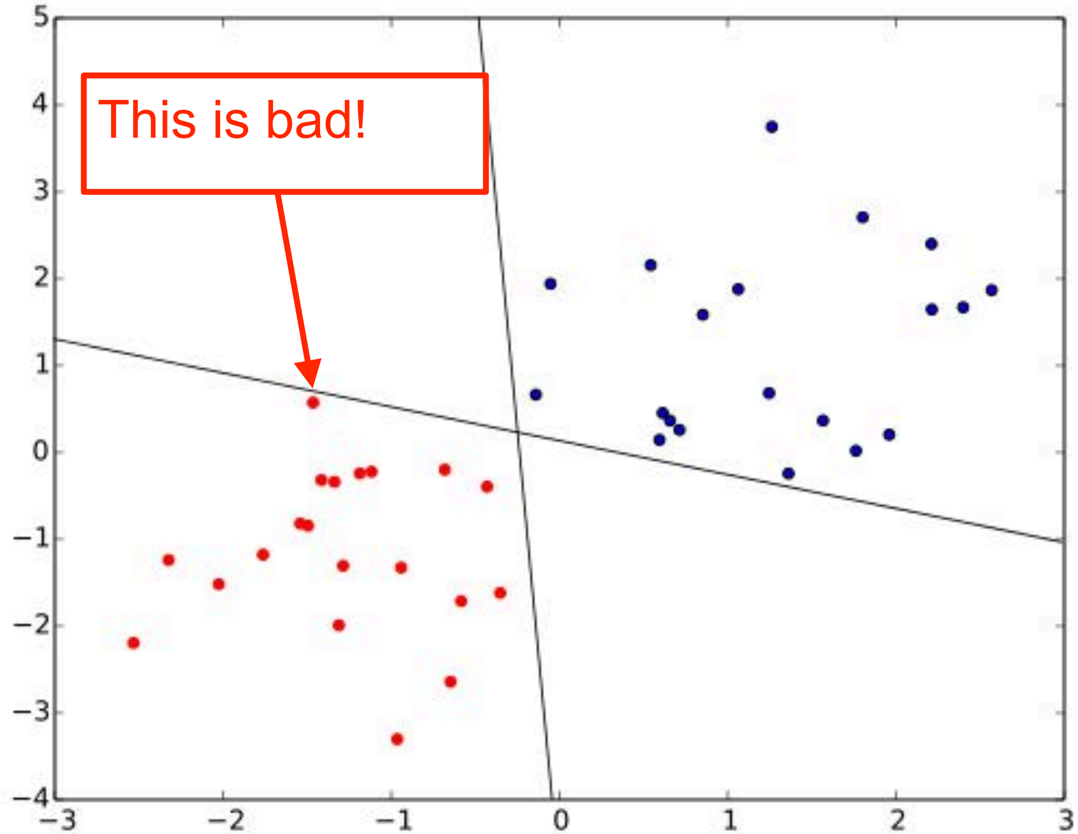


$$y(\mathbf{x};\mathbf{w},w_0) = \begin{cases} 1 & \text{if} \quad \mathbf{w}^T\mathbf{x} + w_0 \geq 0\ , \\ -1 & \text{otherwise.} \end{cases}$$

Given the training set $\{(x_n, t_n)_{1\leq n\leq N}\}$, choose a $\mathbf{w}$ that minimizes

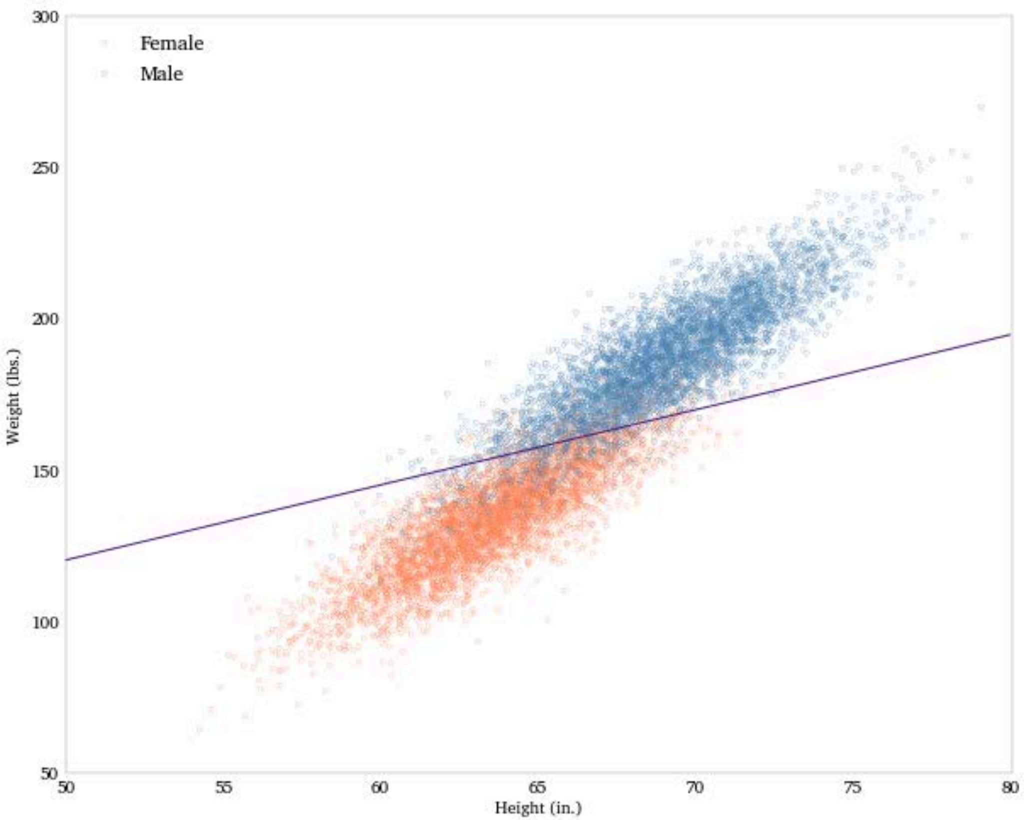
$$E(\mathbf{w}, w_0) = -\sum_{n=1}^{N}(\mathbf{w}^T\mathbf{x}_n + w_0)t_n$$

The Problem with the Perceptron

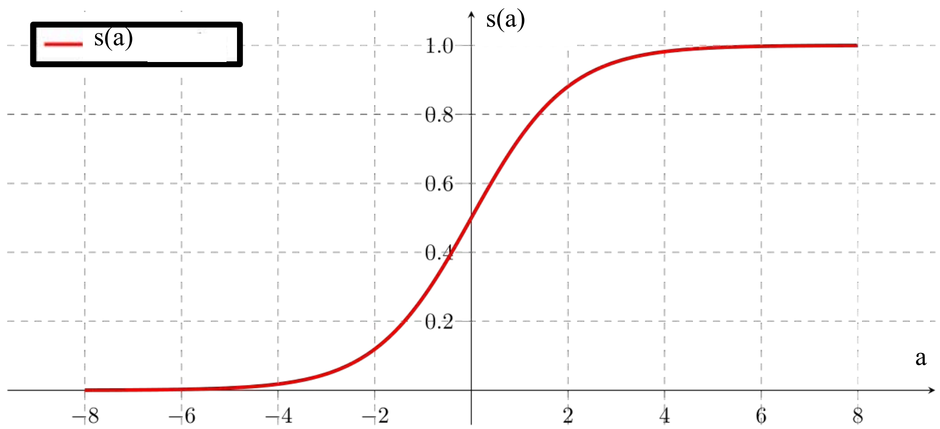


- Two different solutions among infinitely many.
- The perceptron has no way to favor one over the other.

Logistic Regression



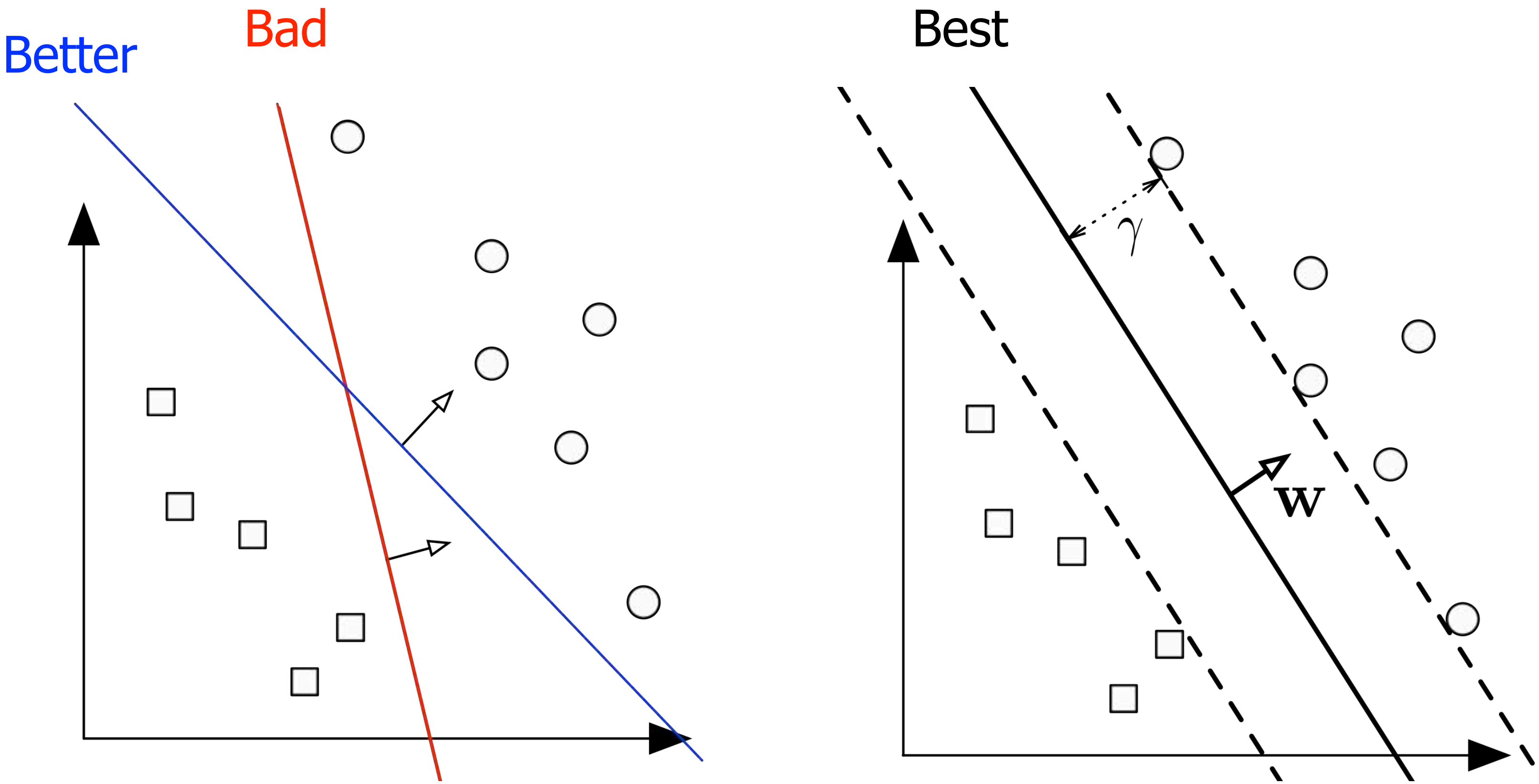
$$y(\mathbf{x}; \mathbf{w}, w_0) = \sigma(\mathbf{w}^T \mathbf{x} + w_0)$$
$$\approx p(t = 1, \mathbf{x})$$



Given the training set $\{(x_n, t_n)_{1 \leq n \leq N}\}$, choose a $\mathbf{w}$ that minimizes

$$E(\mathbf{w}, w_0) = -\sum_n \{t_n \ln y_n + (1 - t_n) \ln(1 - y_n)\} \approx -\ln(p(\mathbf{t}|\mathbf{w}, w_0)) \ .$$

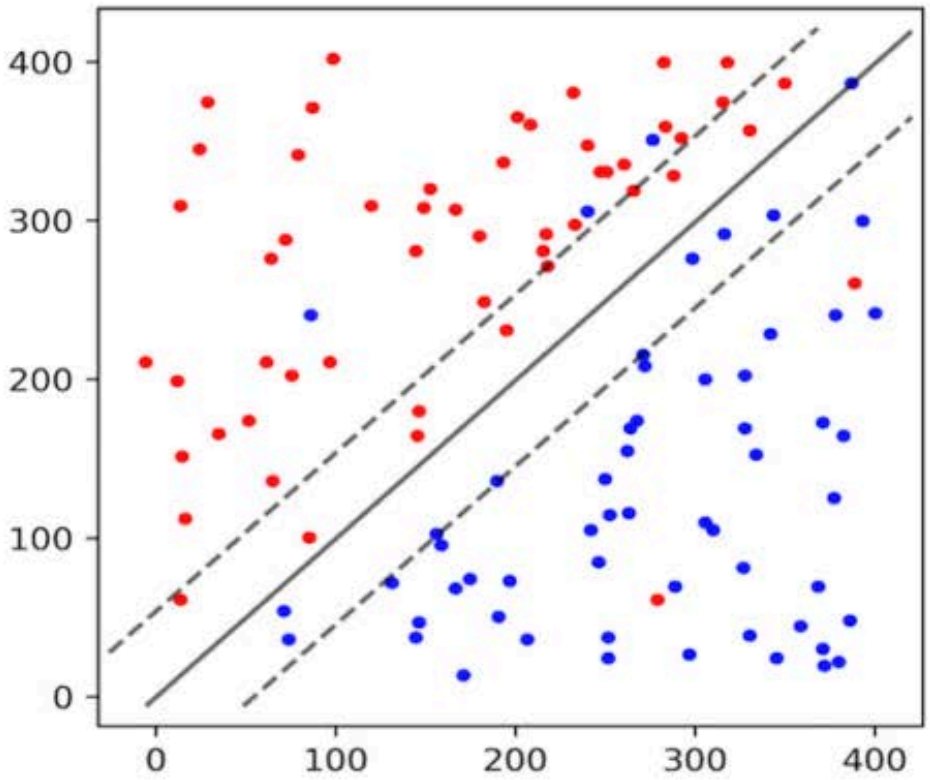
Maximizing the Margin



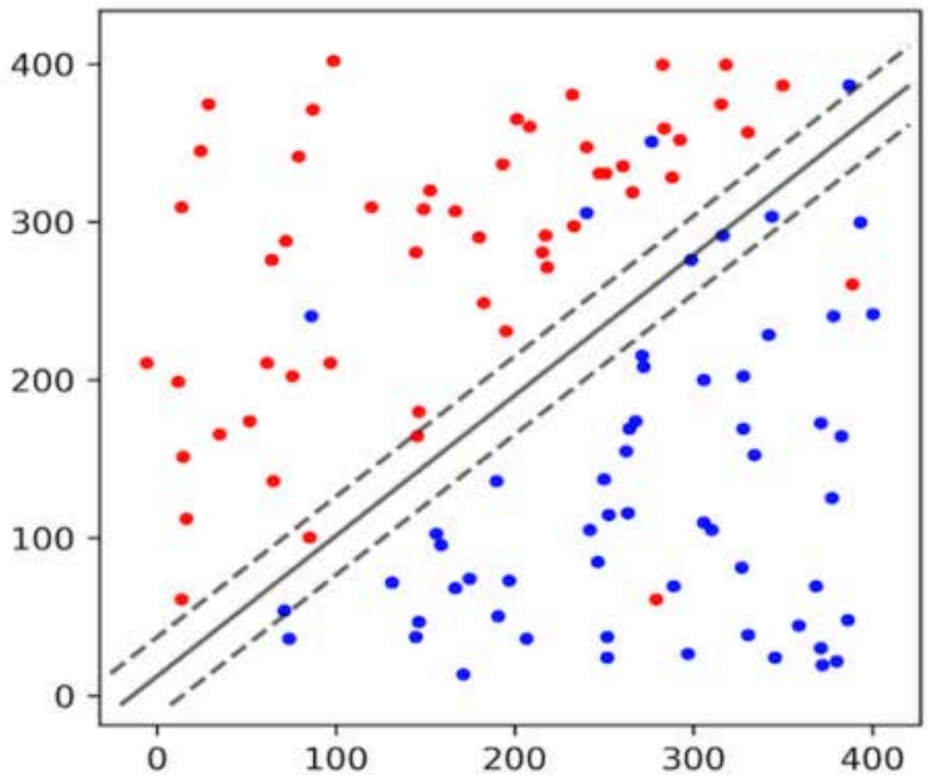
- The larger the margin, the better!
- In the presence of outliers, the logistic regression does not guarantee a large one.

How do we maximize it?

Max Margin Classifier



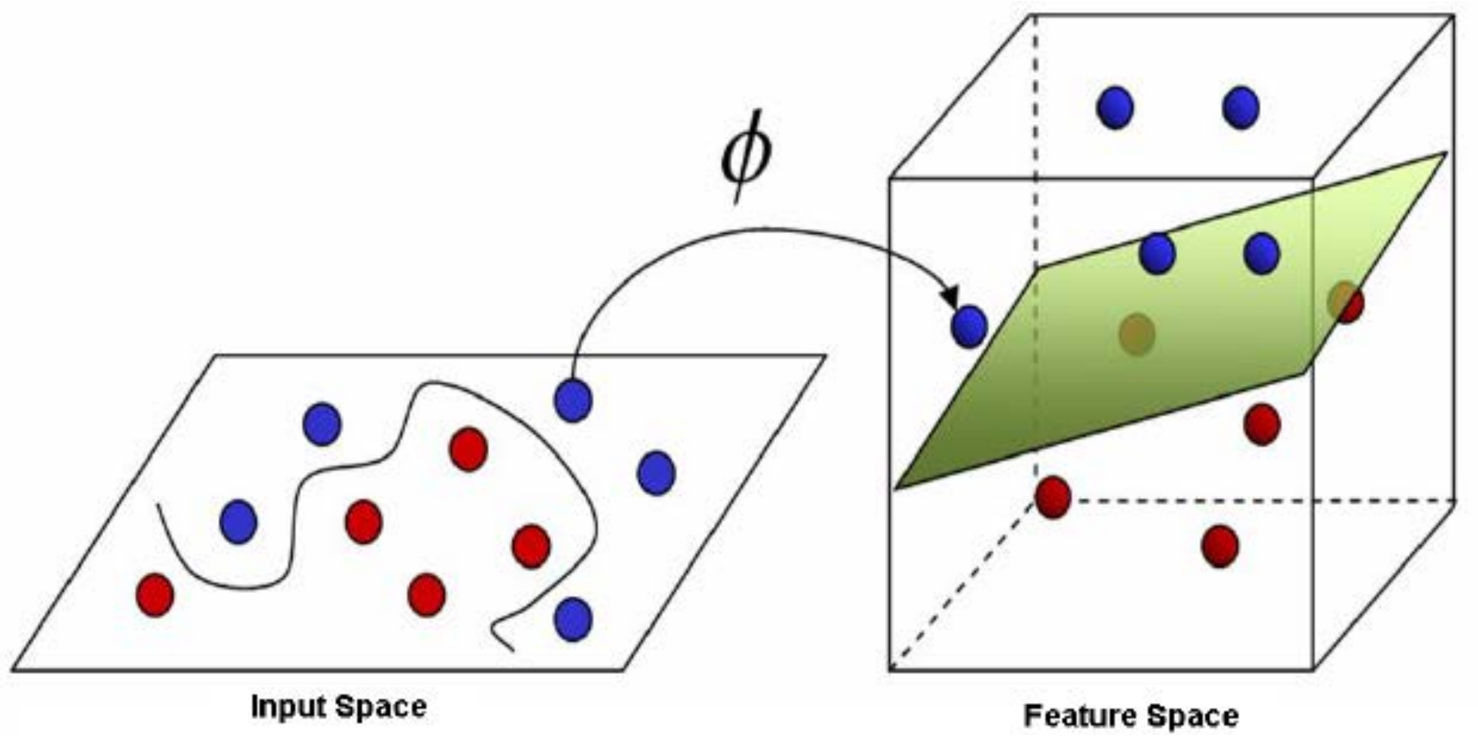
C=1:
- Large margin.
- Many training samples misclassified.



C=100:
- Small margin.
- Few training samples misclassified.

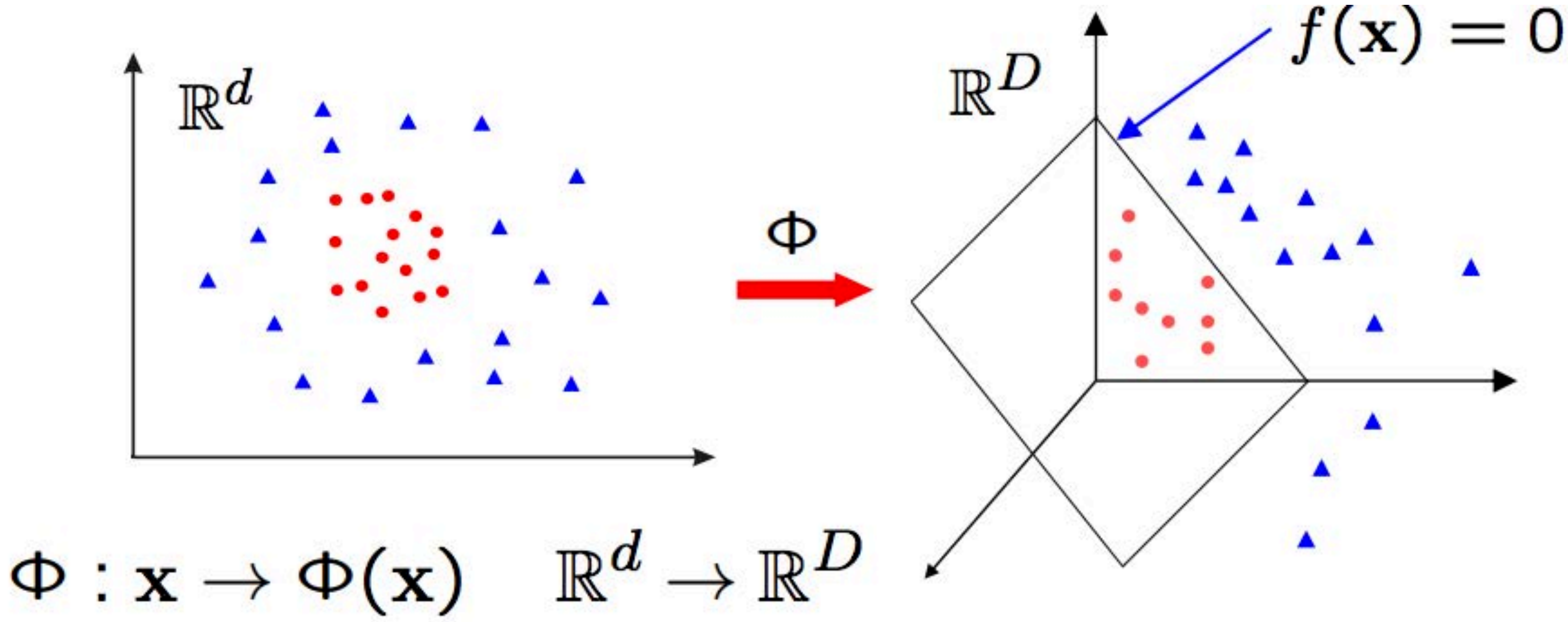
Which is best?
- It depends.
- Must use cross-validation, as we did for k-Means.

Non Linearly Separable Data



- Map to a higher dimensional space in which it is.
- Use an ensemble of classifiers.
- Use a deep network.

Classification in Feature Space



- Map from R^d to R^D
- Learn a linear classifier in R^D

$$y(\mathbf{x}) = \sigma(\mathbf{w}^T \phi(\mathbf{x}) + w_0)$$

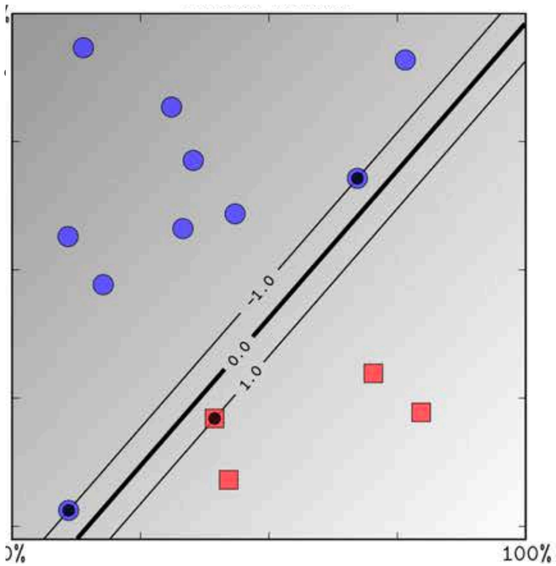
$$\phi : \mathbb{R}^d \to \mathbb{R}^D$$

Polynomial SVMs

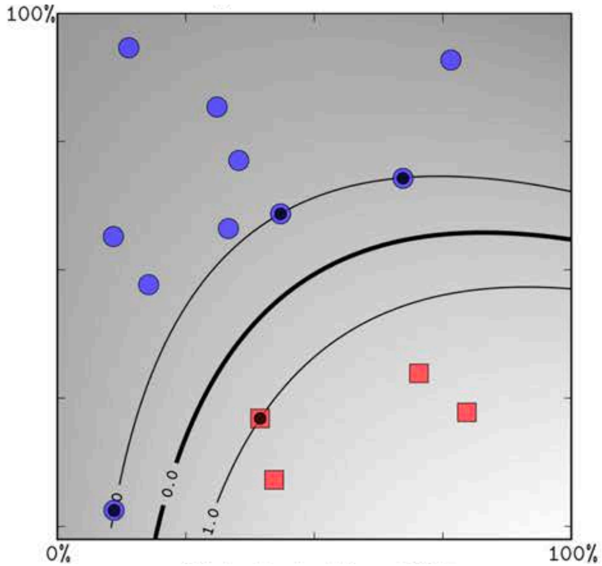
$$\mathbf{w}^* = min_{(\mathbf{w},\{\xi_\mathbf{n}\})}\frac{1}{2}||\mathbf{w}||^2 + C\sum_{n=1}^{N}\xi_n,$$

$$\text{subject to } \forall n, \quad t_n \cdot (\tilde{\mathbf{w}} \cdot \phi(\mathbf{x}_n)) \geq 1 - \xi_n \text{ and } \xi_n \geq 0.$$

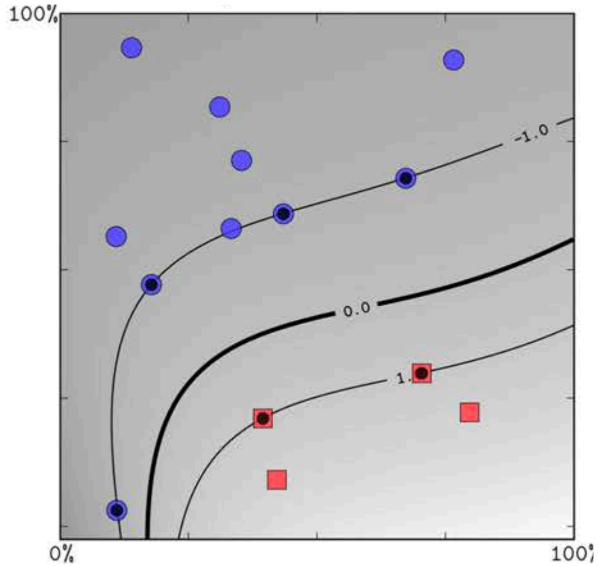
- C is constant that controls how costly constraint violations are.



M =1

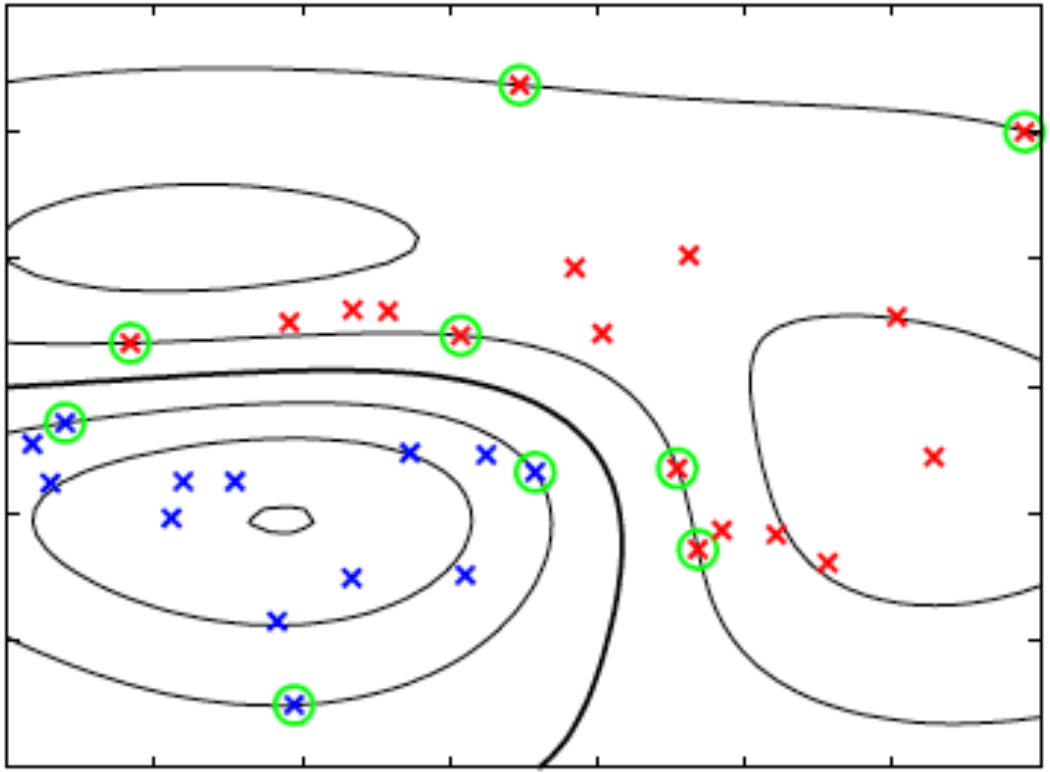


M = 2



M = 5

Kernel SVMs



$$\mathbf{w} = \sum_{n=1}^{N} a_n t_n \phi(\mathbf{x}_n) \; .$$

$$y(\mathbf{x}) = \mathbf{w}^T \phi(\mathbf{x}) + b \; ,$$

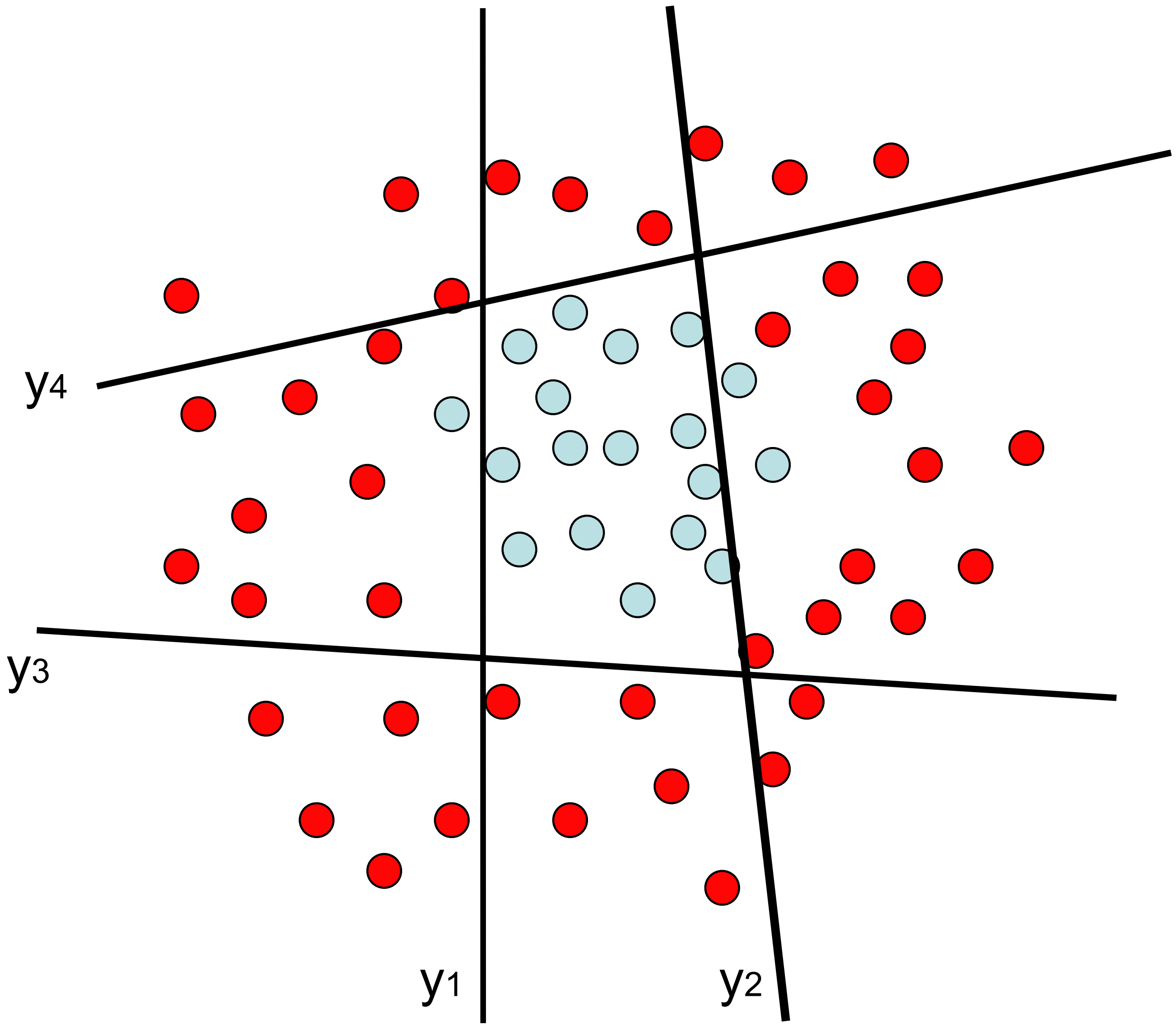
$$= \sum_{n=1}^{N} a_n t_n k(\mathbf{x}, \mathbf{x}_n) + b \; ,$$

with $k(\mathbf{x}, \mathbf{x}') = \phi(\mathbf{x})^T \phi(\mathbf{x}')$.

- Only for a subset of the data points is a_n is non zero.
- The corresponding x_n are the support vectors and satisfy $t_n y(x_n)=1$.
- They are the only ones that need to be considered as test time.

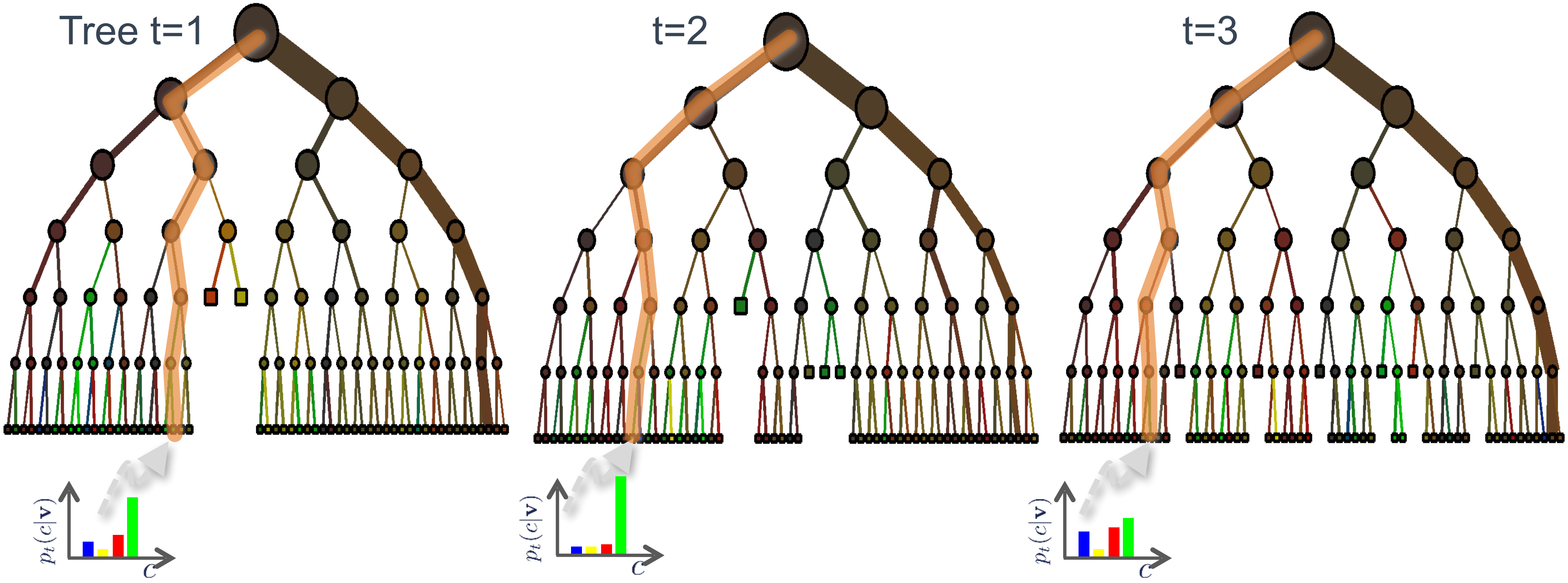
—> That is what makes SVMs practical!

AdaBoost

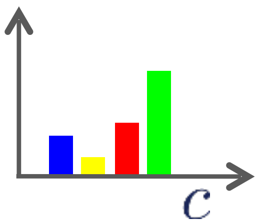


$$y(\mathbf{x}) = \alpha_1 y_1(\mathbf{x}) + \alpha_2 y_2(\mathbf{x}) + \alpha_3 y_3(\mathbf{x}) + \alpha_4 y_4(\mathbf{x})$$

Decision Forests

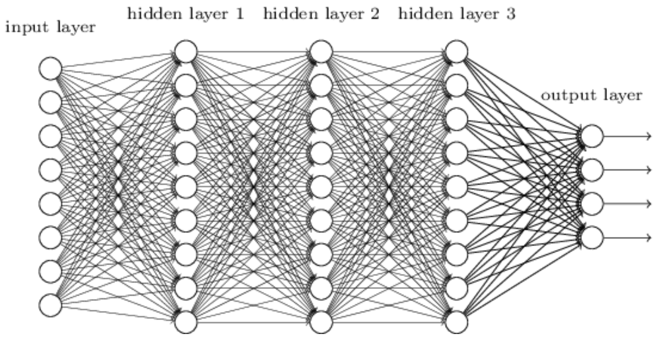


$$L(c, \mathbf{v}) = \frac{1}{T} \sum_t - \log(p_t(c|\mathbf{v}))$$

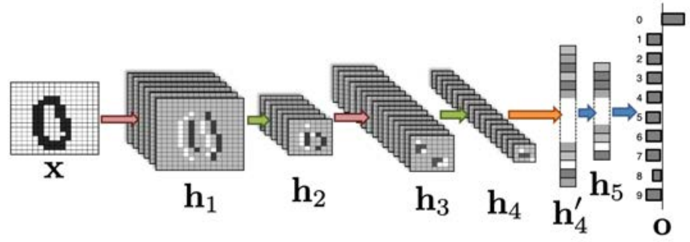


Simple and flexible approach.

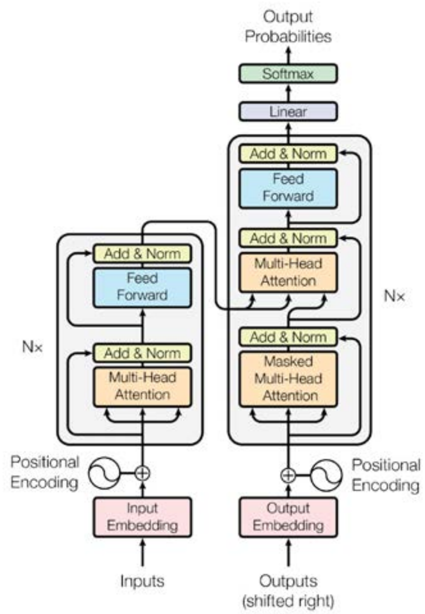
Neural Networks



Fully connected



Convolutional



Transformers

- Some of the most powerful techniques around when enough training data is available.
- Convolutional Neural Nets are particularly well adapted for image processing.
- Transformers excel at natural language processing but are also very good for image processing

Regression Techniques

- Linear Regression
- Polynomial Regression
- Neural Networks

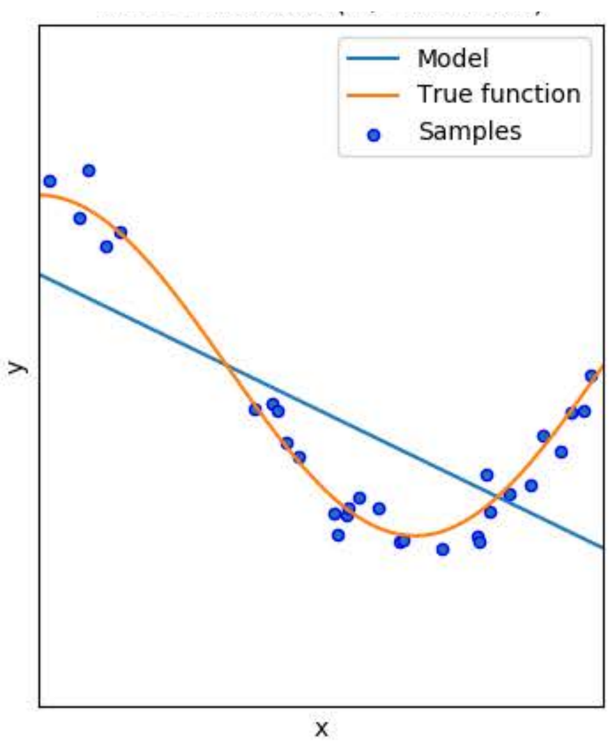
Supervised Regression

$$\text{Minimize } E(\mathbf{w}) = \sum_{n=1}^{N} L(y(\mathbf{x}_n; \mathbf{w}), t_n)$$

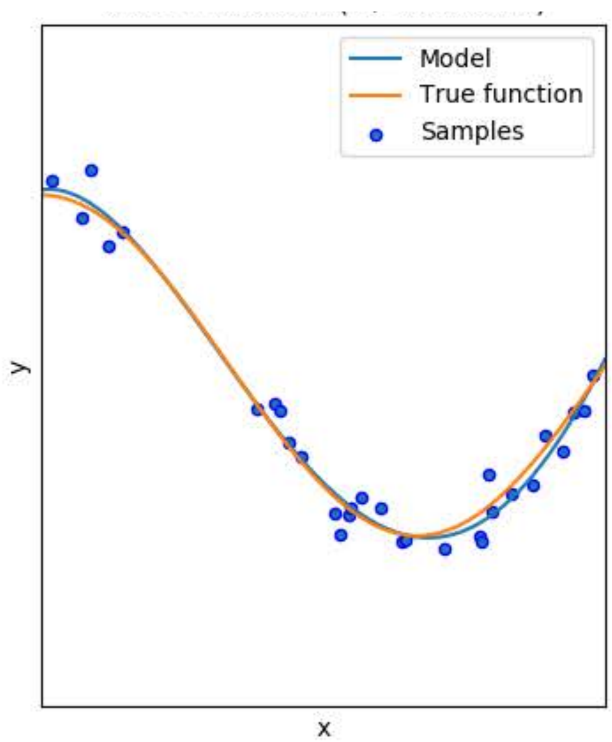
- **x:** Feature vector
- **w:**Model parameters
- t: Label
- y: Predictor
- L: Loss Function
- E: Error Function

Same as for classification, except for the fact that the t_n now denotes continuous values!

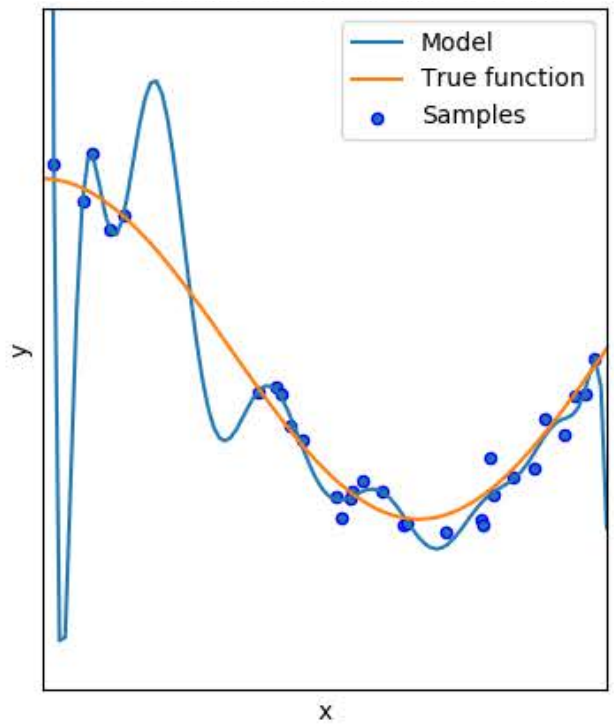
Linear and Non-Linear Regression



Order 1



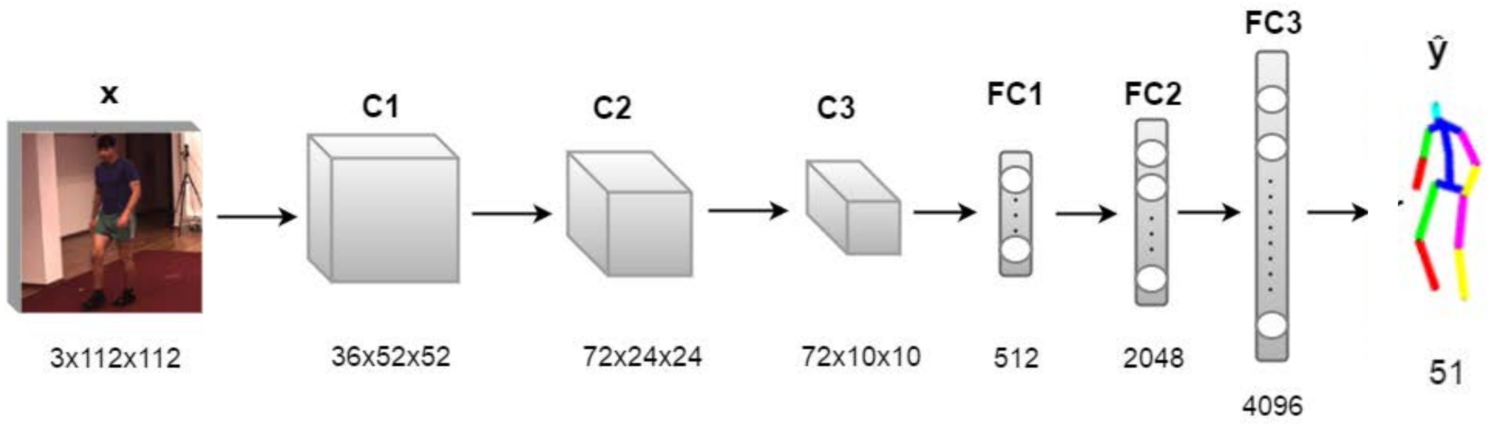
Order 4



Order 15

The trick is to find the best compromise between simplicity and goodness of fit.

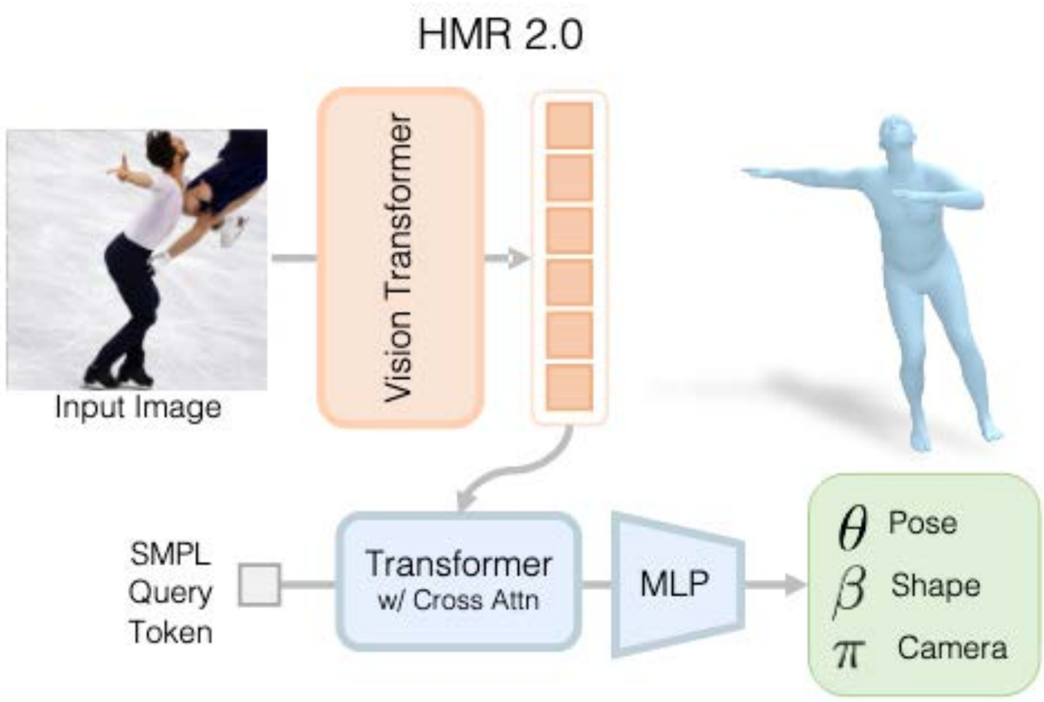
Deep Networks



Input: $\mathbf{I}$

Output: $\{\mathbf{y}_j\}_{1\leq j\leq J}$

Tekin et al. CVPR'16

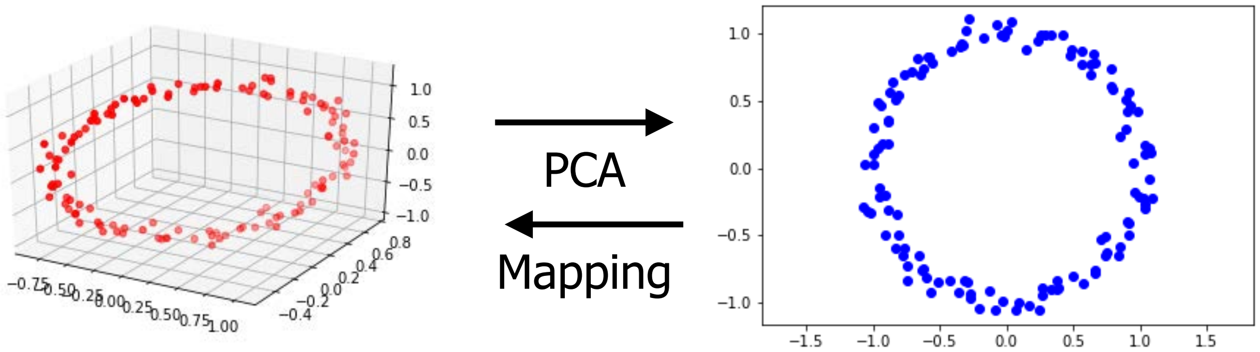


Goel et al. , ICCV'23

Dimensionality Reduction Techniques

- PCA
- LDA
- Autoencoders

PCA



$\mathbf{x}$

$\mathbf{y} = \mathbf{W}^{\mathbf{T}}(\mathbf{x} - \bar{\mathbf{x}})$

$\hat{\mathbf{x}} = \bar{\mathbf{x}} + \mathbf{W}\mathbf{y}$

- This mapping incurs some loss of information.
- However, the corresponding rectangular matrix **W** is the orthogonal matrix that minimizes the reconstruction error

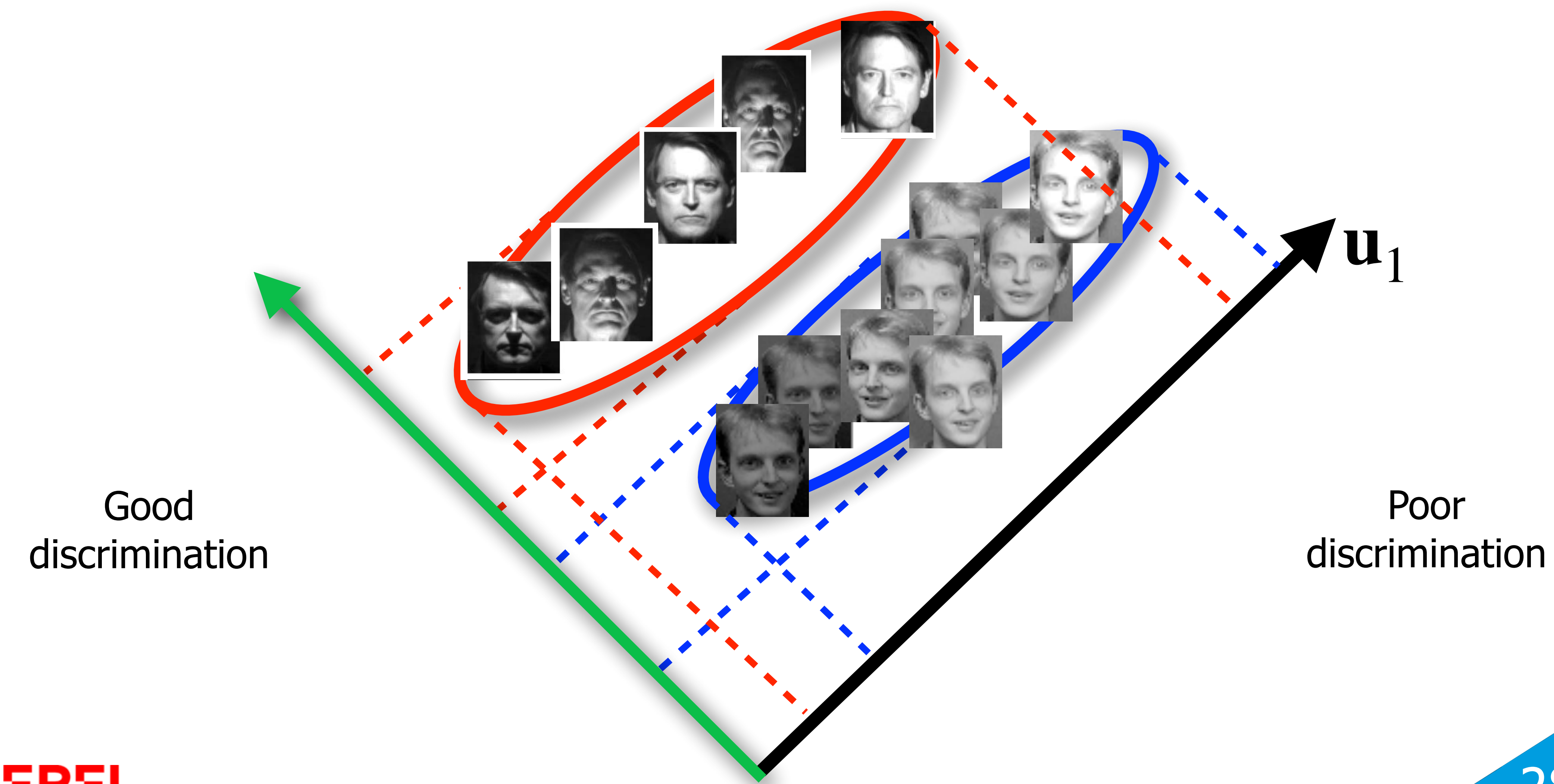
$$e = \|\hat{\mathbf{x}} - \mathbf{x}\|^2$$

where

$$\hat{\mathbf{x}} = \bar{\mathbf{x}} + \mathbf{W}\mathbf{y} = \bar{\mathbf{x}} + \mathbf{W}\mathbf{W}^T(\mathbf{x} - \bar{\mathbf{x}})$$

LDA

Maximise between class variance and minimize within class variance.



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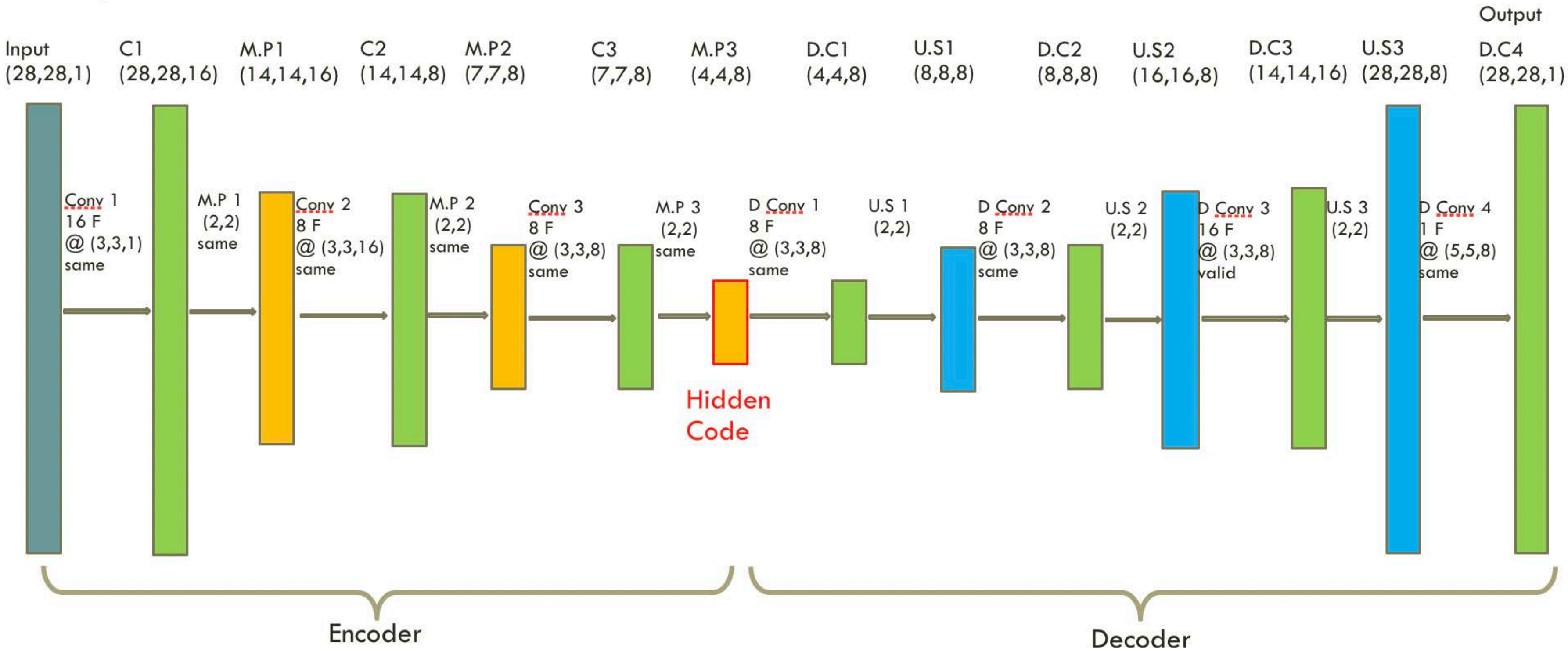
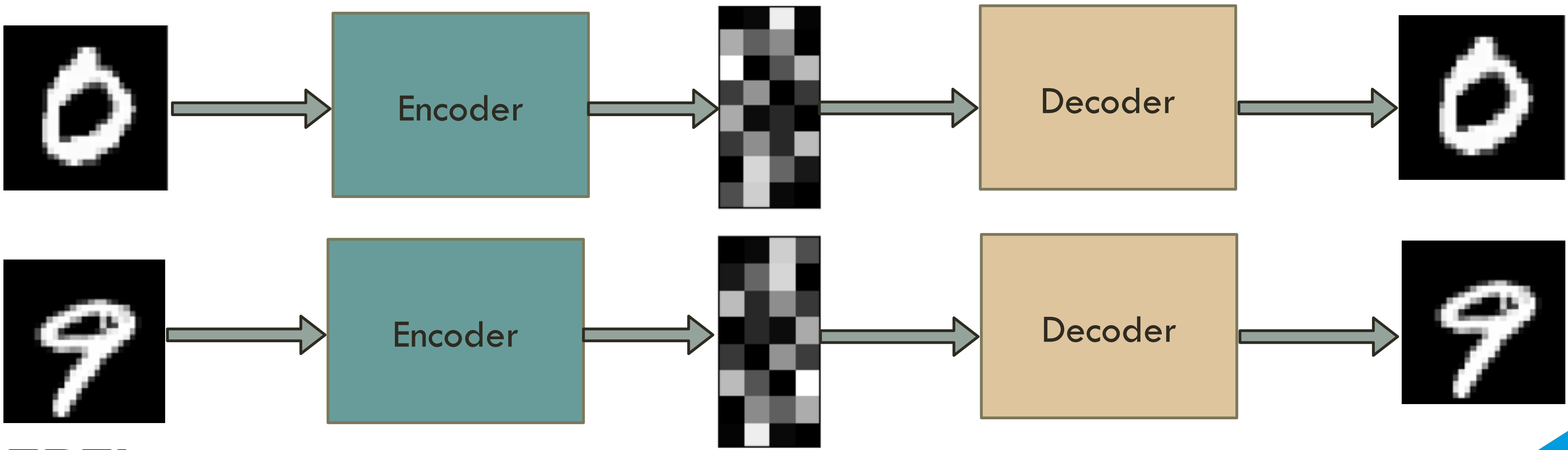
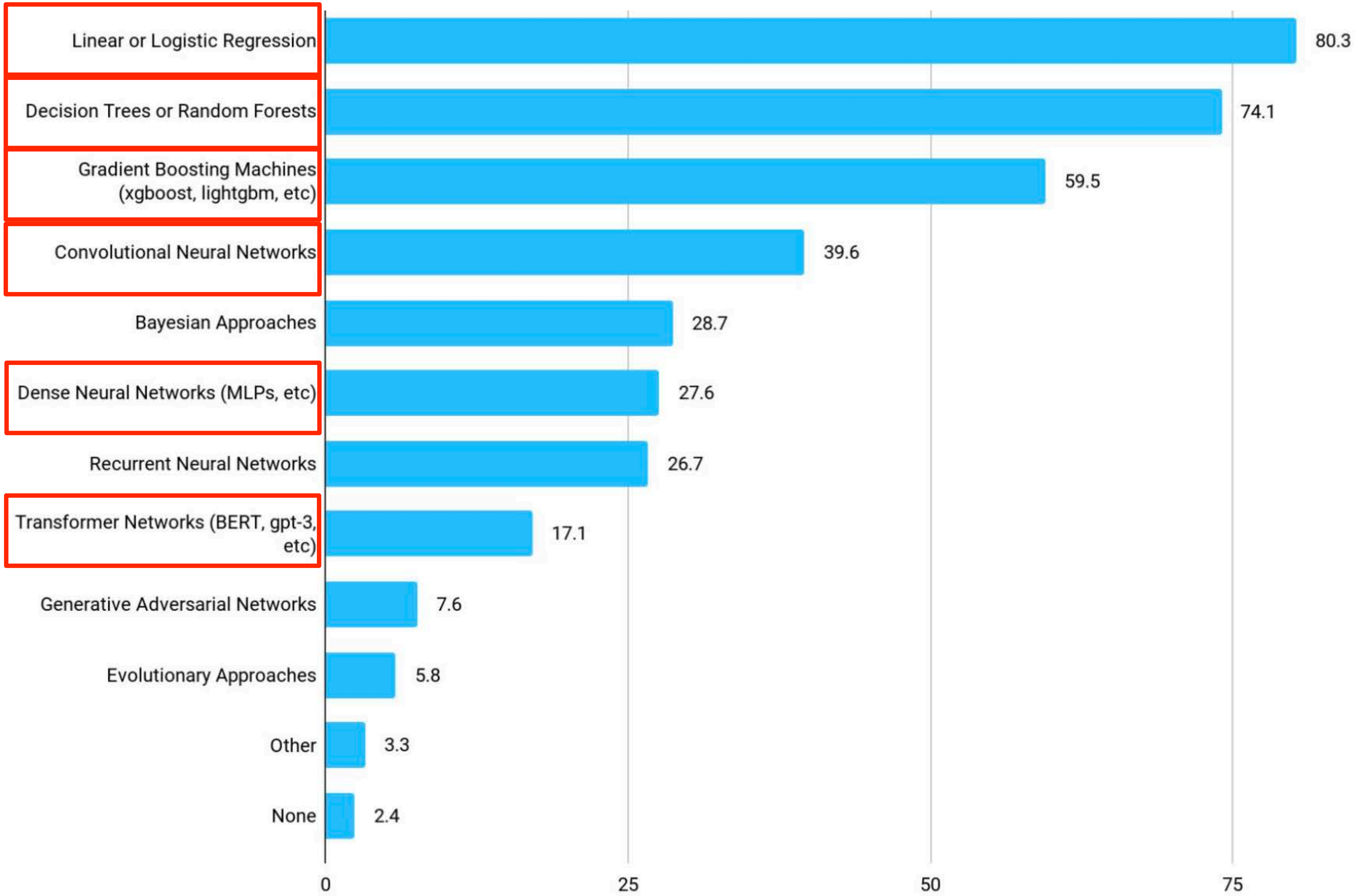
Autoencoders



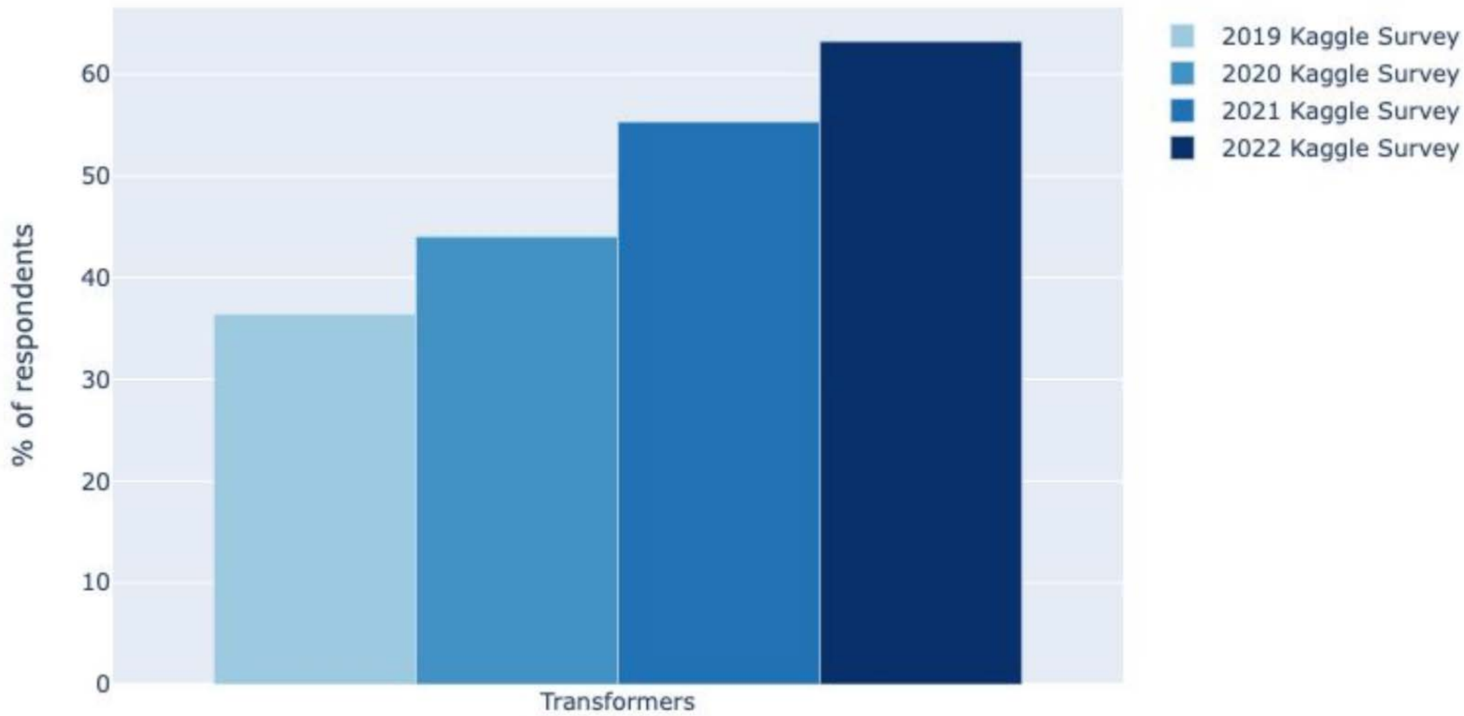


Kaggle Survey (2021)



What data science methods do you use at work?

Kaggle Survey (2022)



- Transformer architectures are becoming more popular for deep learning models?
- Will they dominate?

Time will tell

Logistic Regression on a Massive Scale

Ad Click Prediction at Google:

Methods such as regularized logistic regression are a natural fit for this problem setting. It is necessary to make predictions many billions of times per day and to quickly update the model as new clicks and non-clicks are observed.

—> The simpler methods are not going away and will probably co-exist with the more sophisticated ones.

McMahan et al., KDD '13

In Conclusion

Rule of thumb:

- Small training set: Use GPs.
- Medium training sets: Use boosted trees.
- Large training sets: Use neural nets.
- Enormous training sets: Use transformers

As for all such rules, there are exceptions. Real-time requirements define important ones.

Revisions

Introduction to the Class

- Introduction

Nearest Neighbors

- KNNs
- KMeans

Linear Models

- Linear Classification
- Max Margin Classifiers

⋮

Dimensionality Reduction

- Linear Dimensionality Reduction
- Non Linear Dimensionality Reduction

Conclusion

- Course Summary

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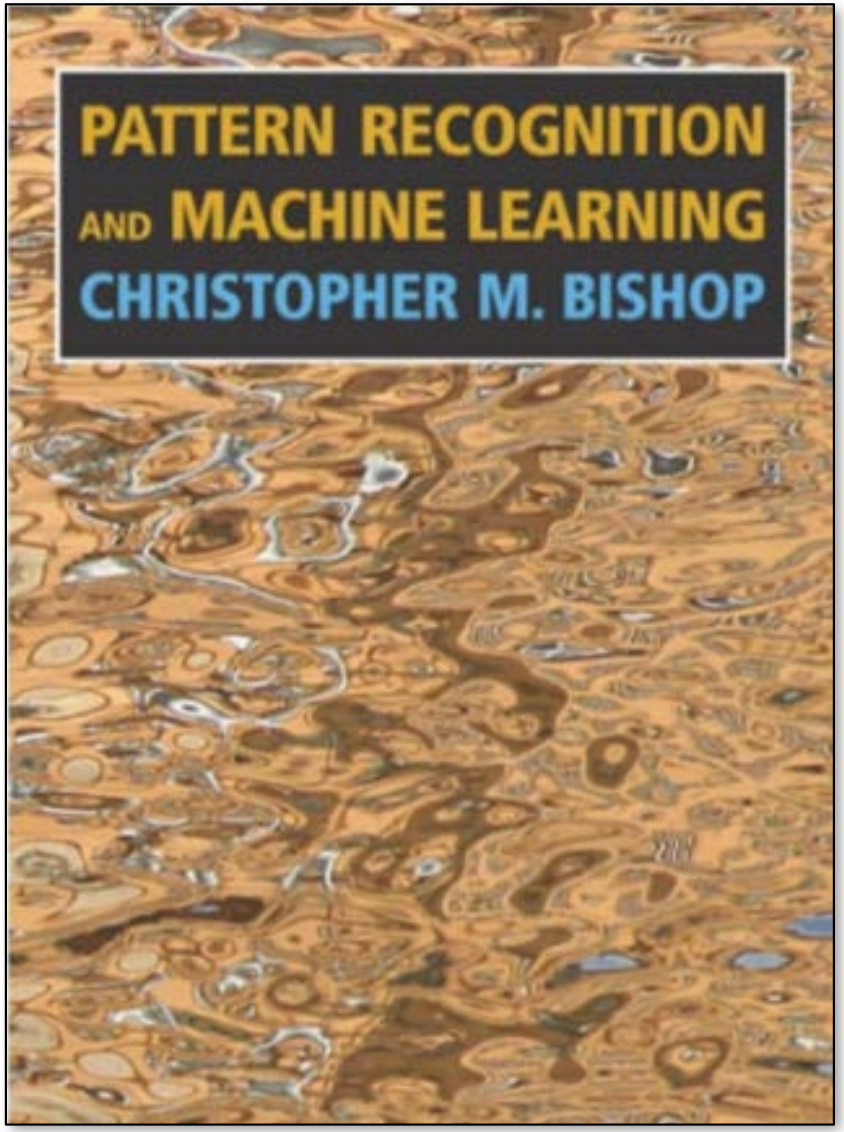

Exam

- On June 30th.
- Possibility of extra-mural exam if you **cannot** come.
- 2.0 hours.
- 1 two-sided **hand-written** A4 page of notes.
- Questions on **non-indented** slides on webpage.

See you then.