

Learning from Images

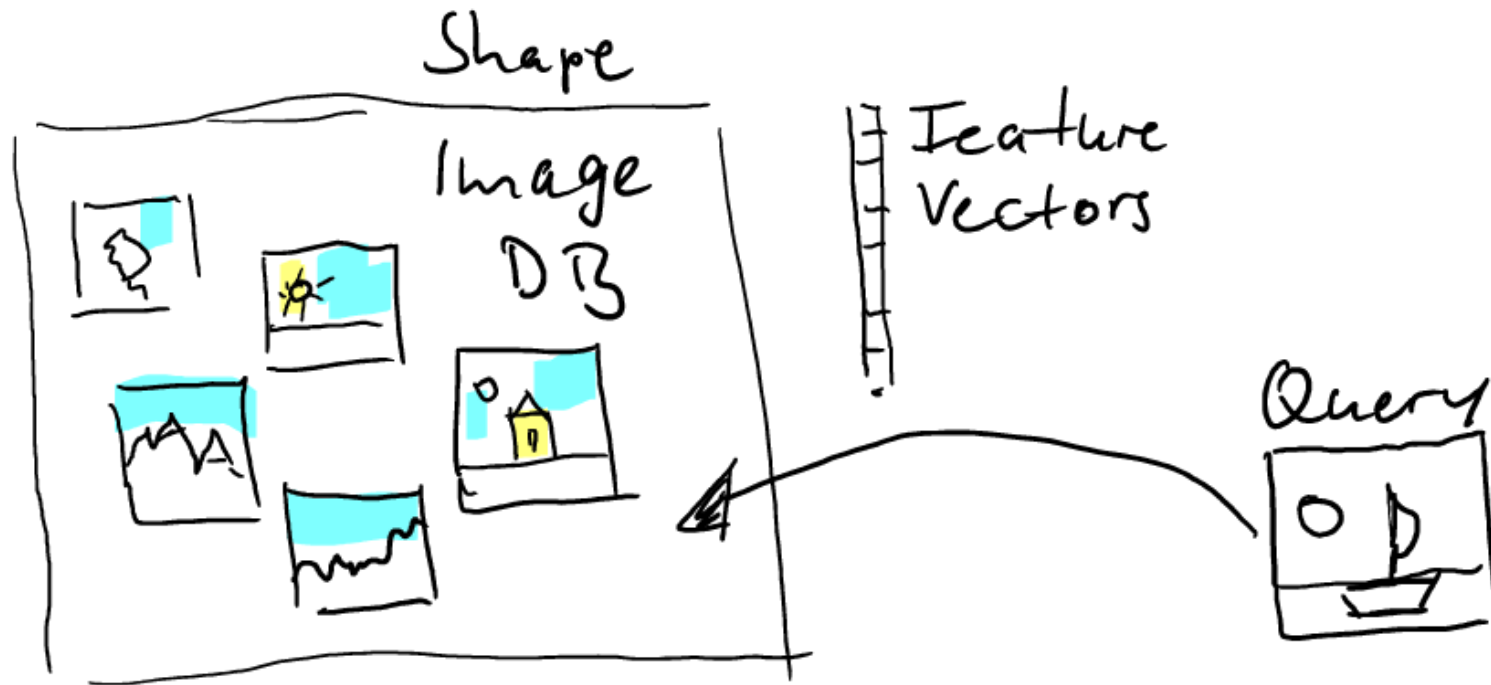
Image Classification

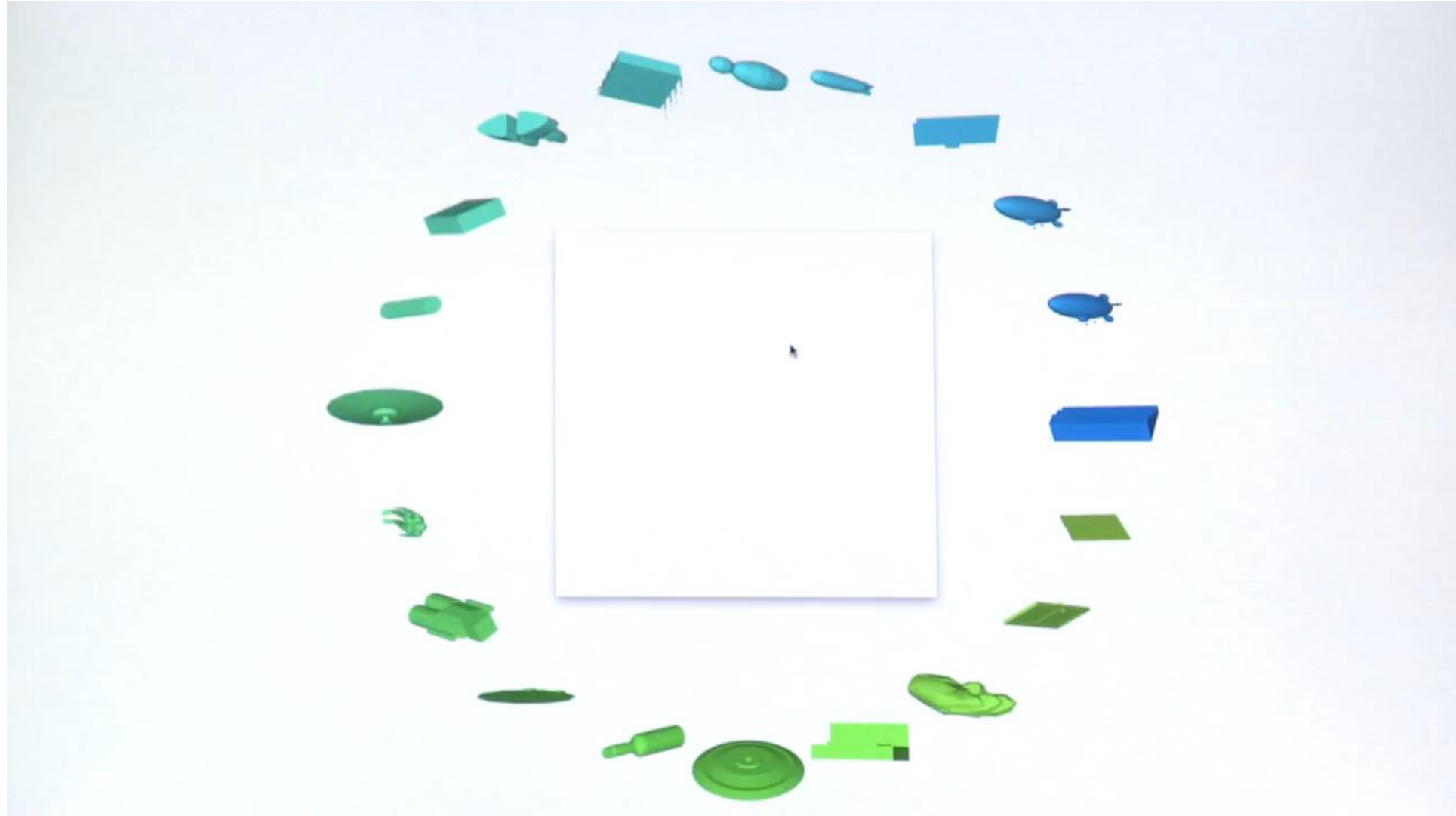
Master DataScience

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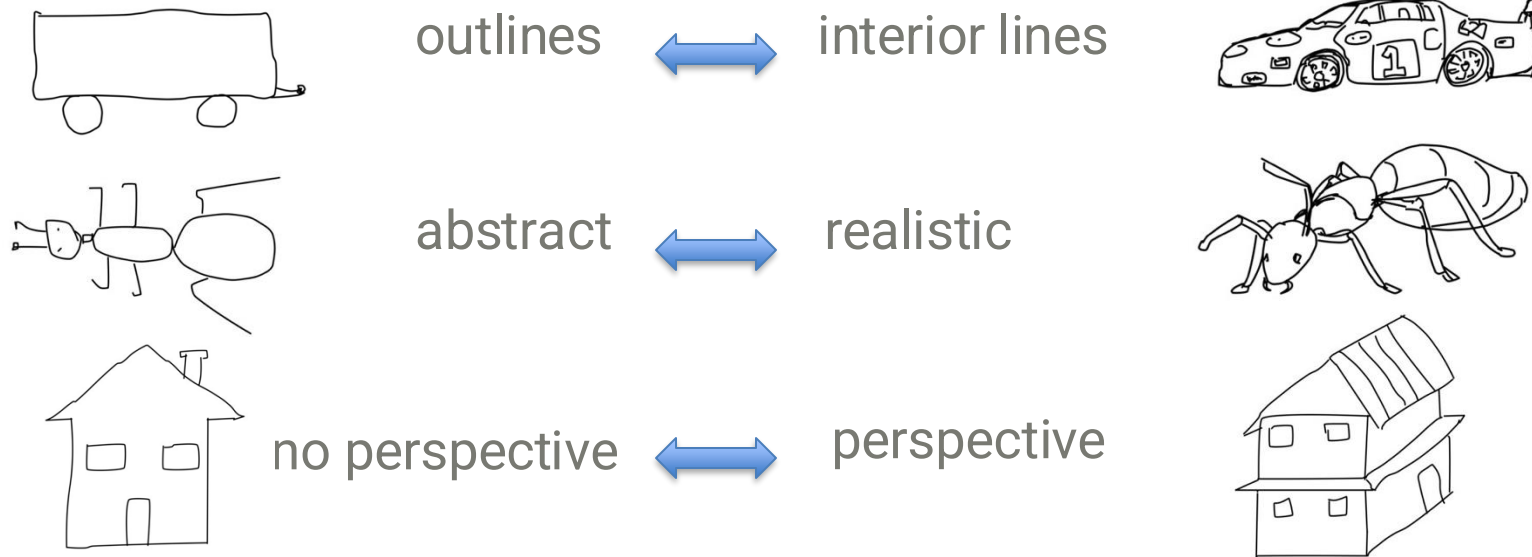
Application I: Image Retrieval



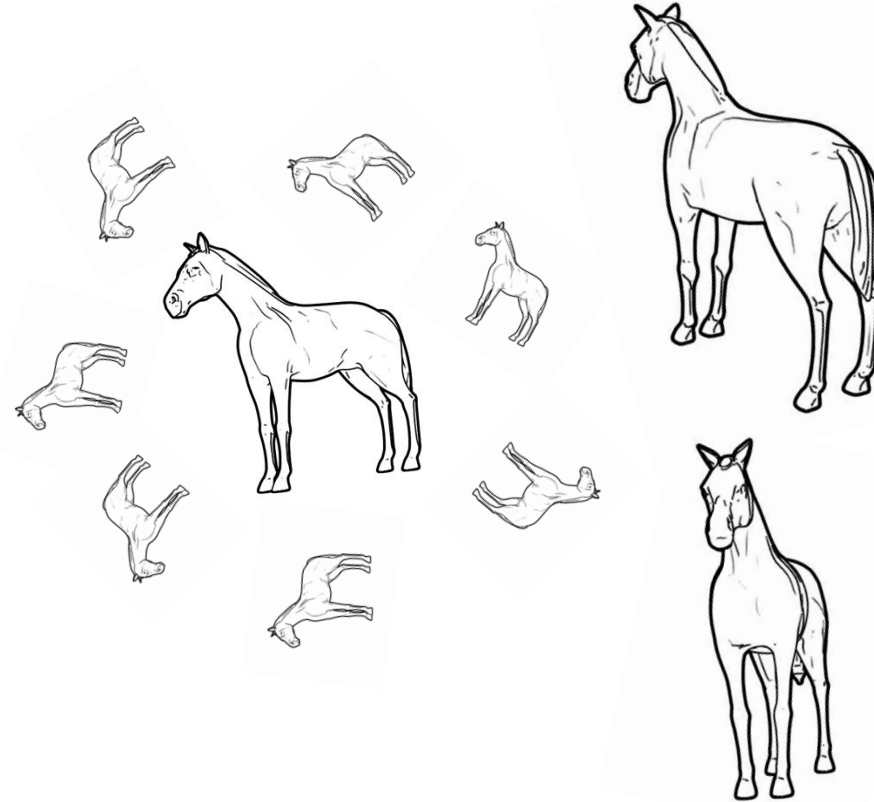
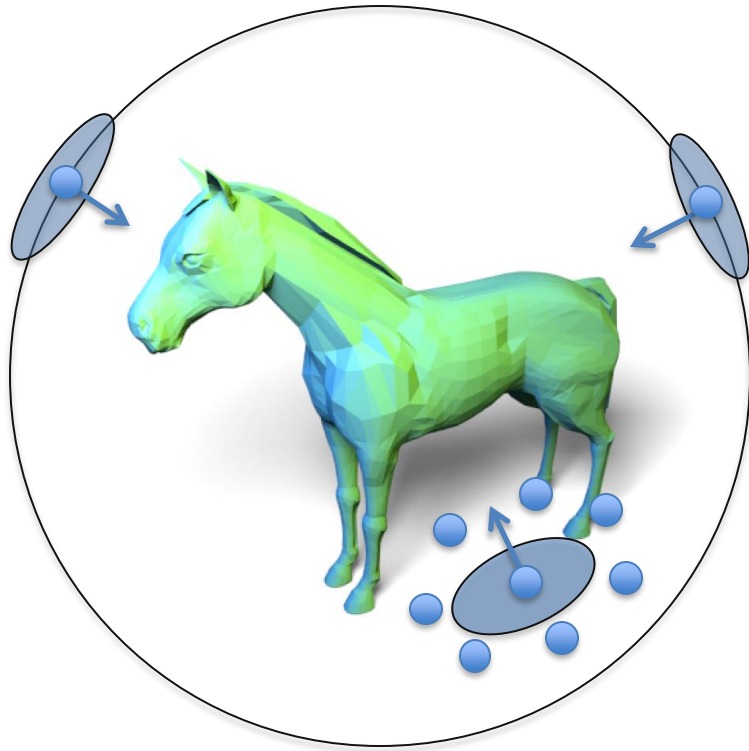


How Do Humans Sketch for Shape Retrieval?

- Large variety of sketching styles:



View Generation

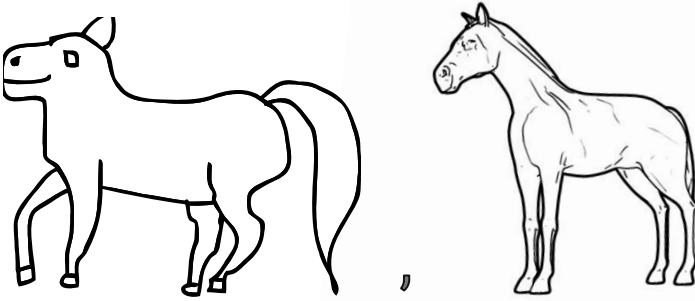


Similarity Measure

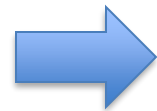
Image-based retrieval



similarity



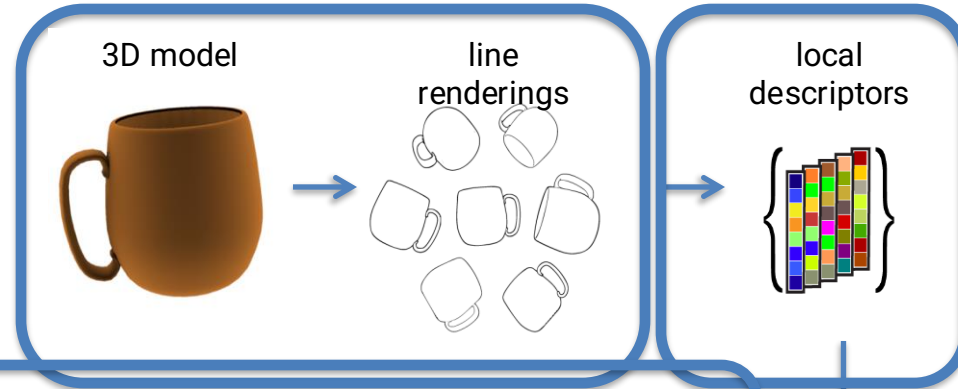
- Requirements:
- Tolerate local and global deformations
 - Support partial matching
 - Fast and efficient



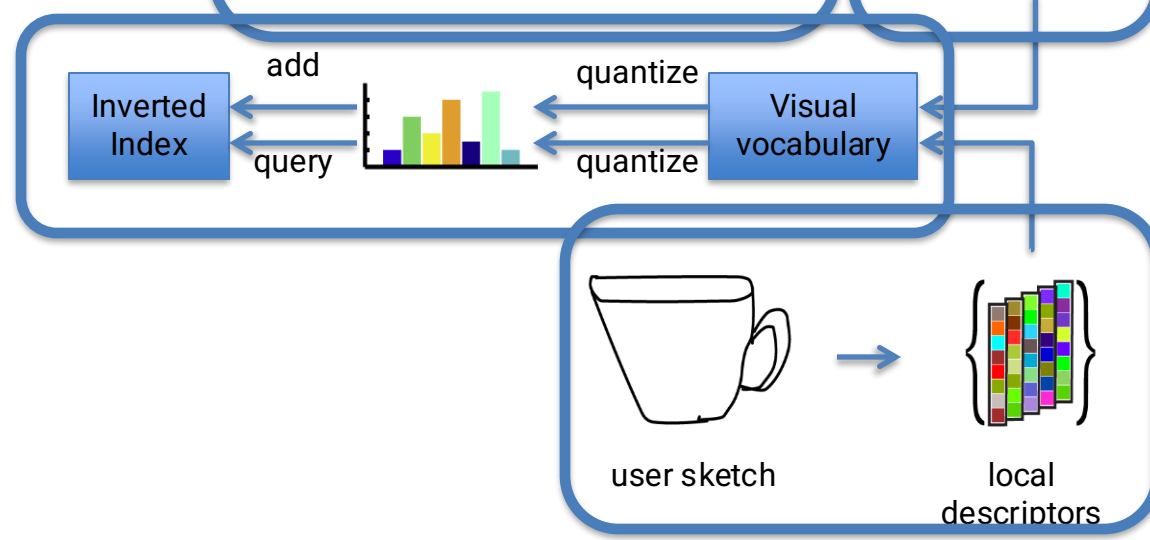
Need appropriate feature transform (descriptor)

Overview Computing Pipeline

Offline Indexing



Online Search

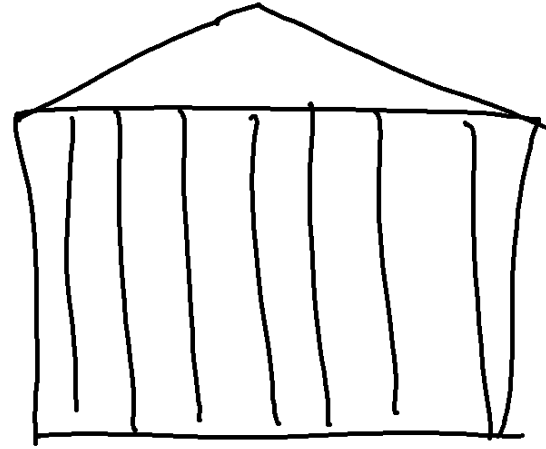


Comparing sketch and image

- Sketches/images represented as feature vector
 - encode essential image/sketch attributes
 - small memory footprint
 - fast to compare

$$\text{dist} \left(\begin{array}{c} \text{Sketch} \\ \text{Image} \end{array} \right) = \left\| \begin{array}{c} 0.21 \\ 0.13 \\ 0.75 \\ 0.31 \\ 0.41 \\ 0.06 \\ 0.93 \\ 0.17 \end{array} - \begin{array}{c} 0.01 \\ 0.17 \\ 0.68 \\ 0.31 \\ 0.44 \\ 0.05 \\ 0.97 \\ 0.13 \end{array} \right\|_m$$

Feature extraction from sketch and image



Feature



Feature

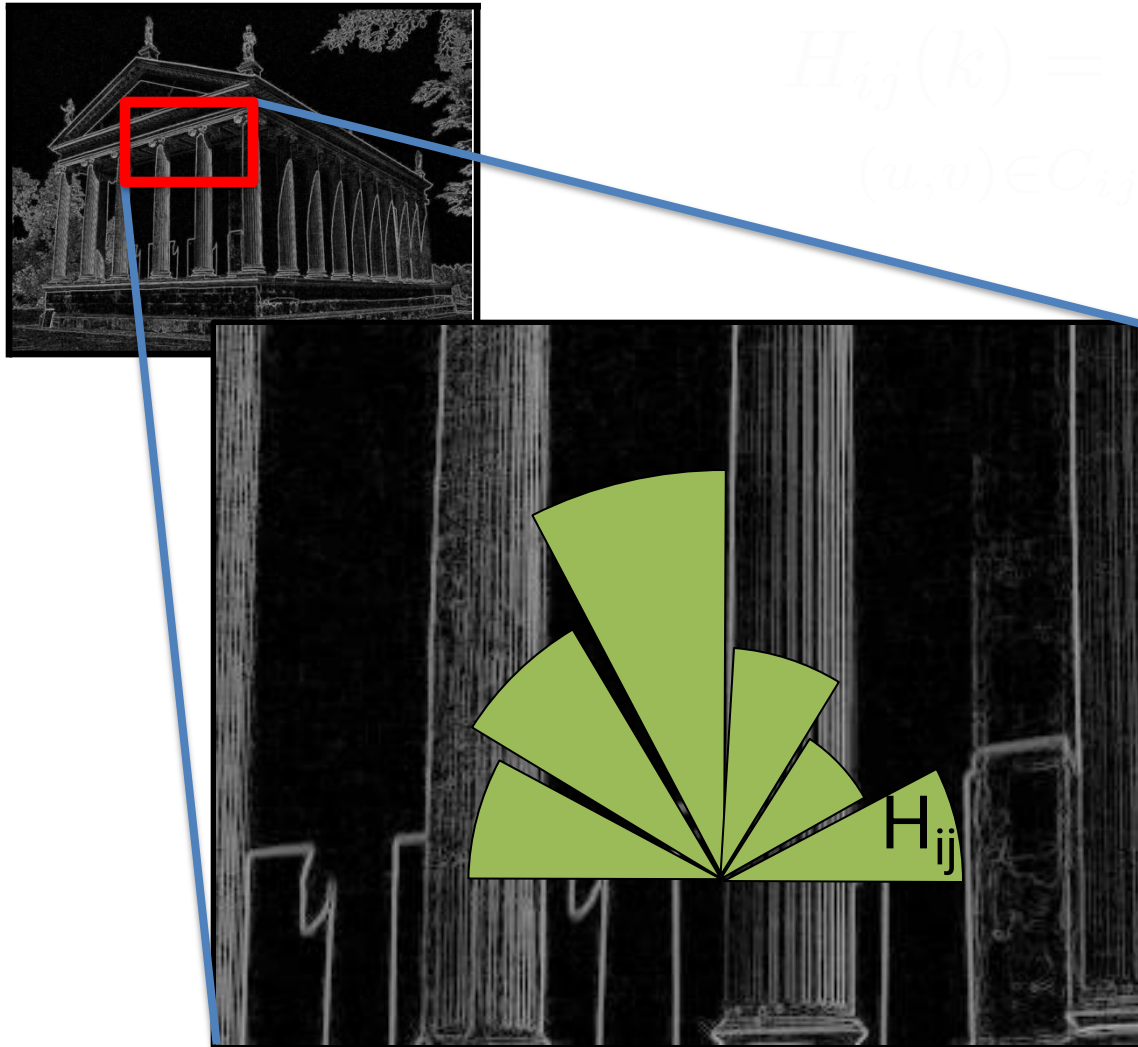


Feature



Edge Histogram Descriptor

Encodes distribution of gradients

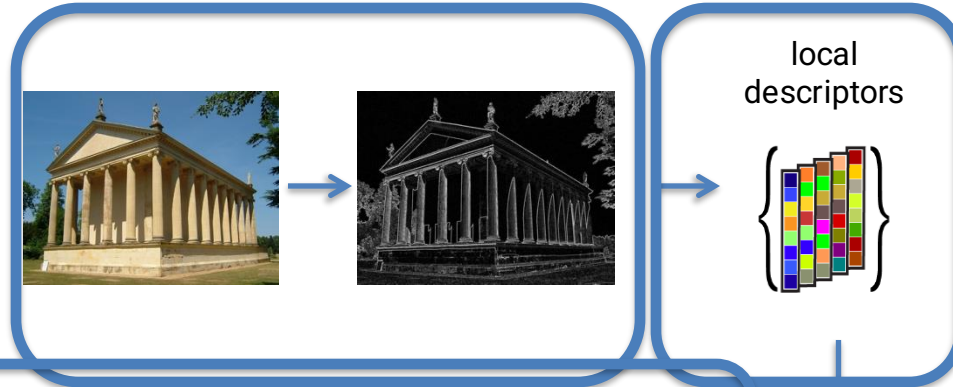


$$H_{ij}(k) = \sum_{(u,v) \in C_{ij}, o(g_{ij}) \in [k/d, k+1/d]} g_{uv}^T g_{uv}$$

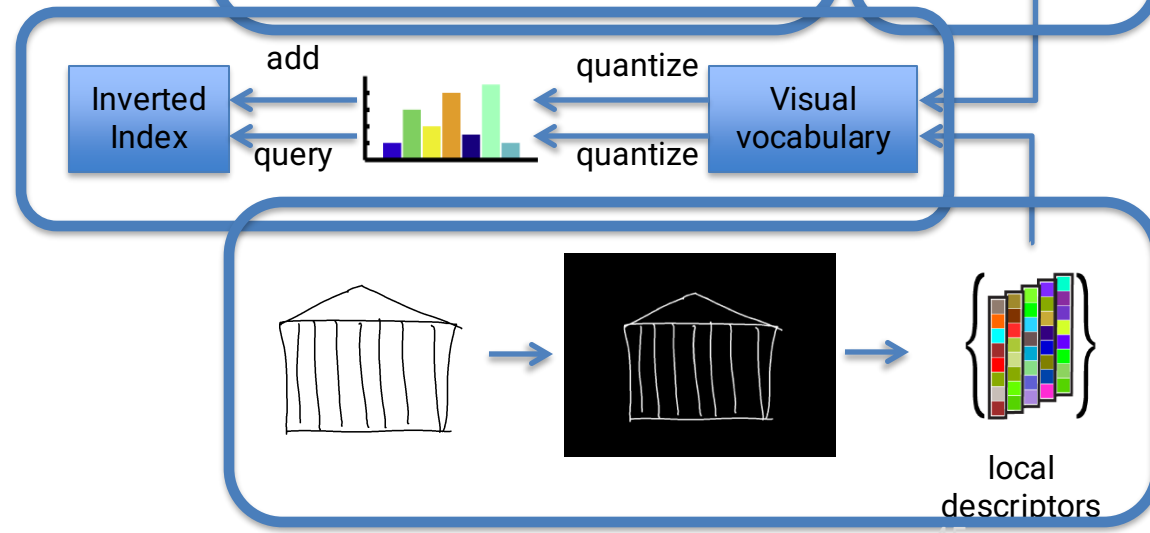


Computing Pipeline

Offline Indexing

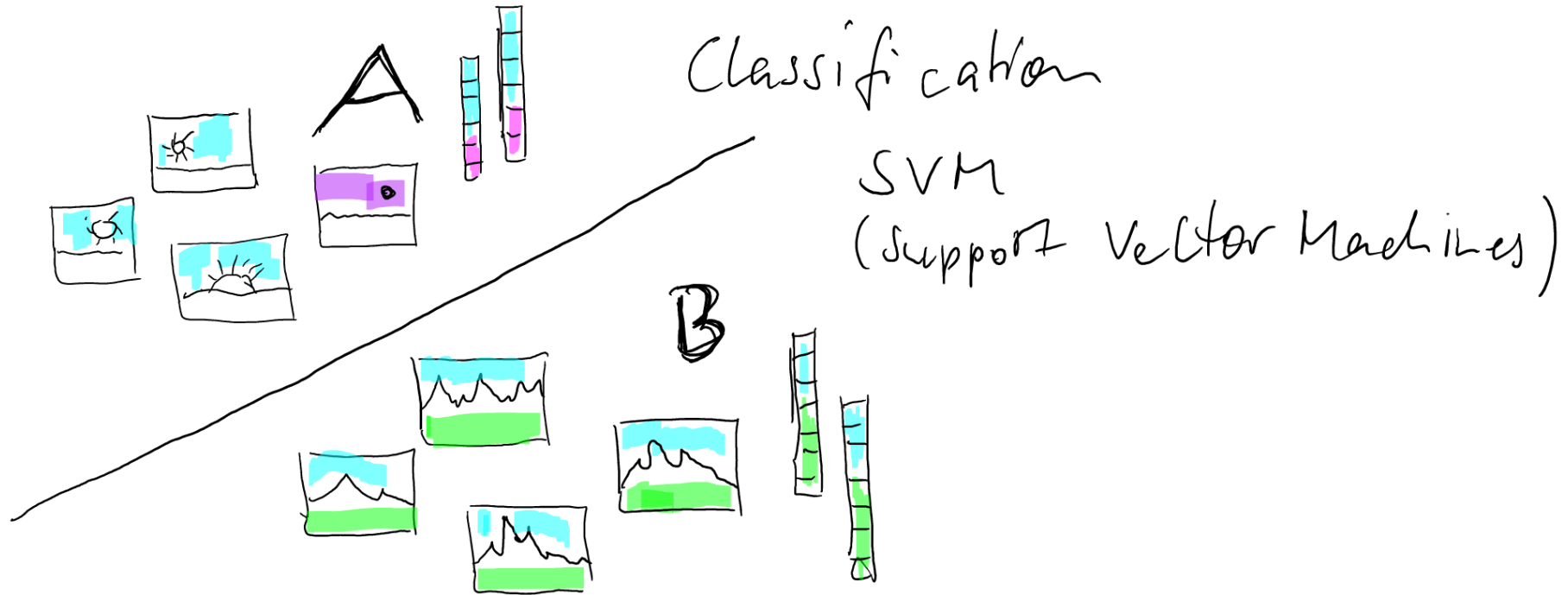


Online Search



Application II: Image Classification

Application II: Image Classification

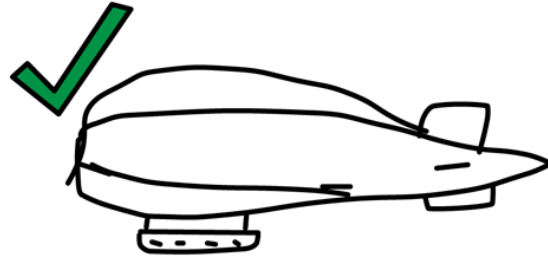


Application II: Image Classification

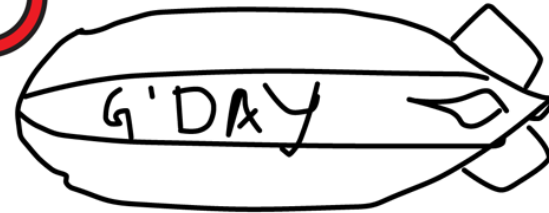


How do users sketch objects?

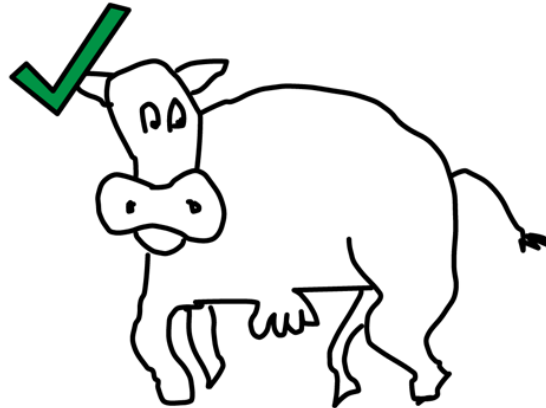
blimp



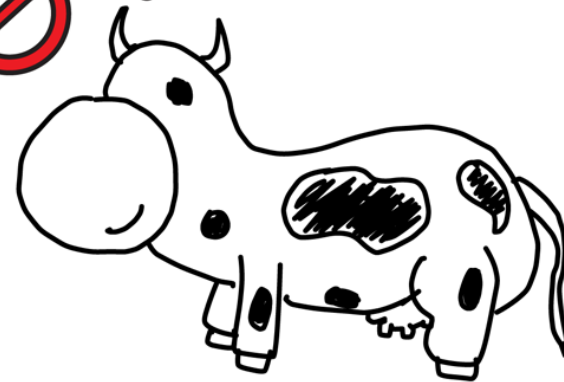
text labels not allowed!



COW

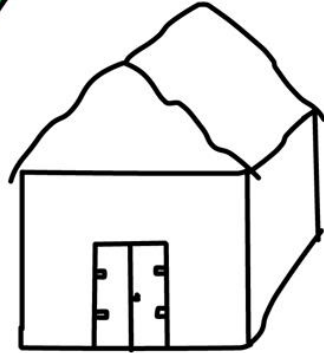


large black areas not allowed!



How do users sketch objects?

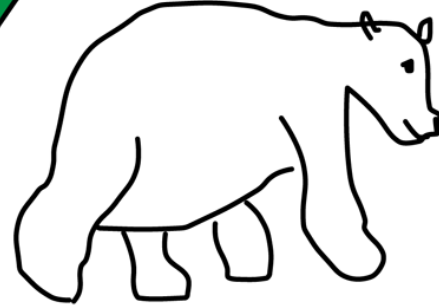
barn



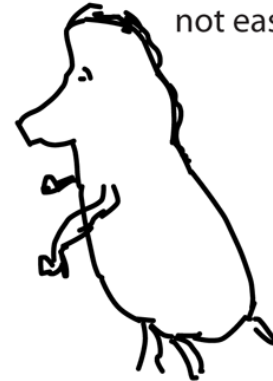
context around object not allowed!



bear

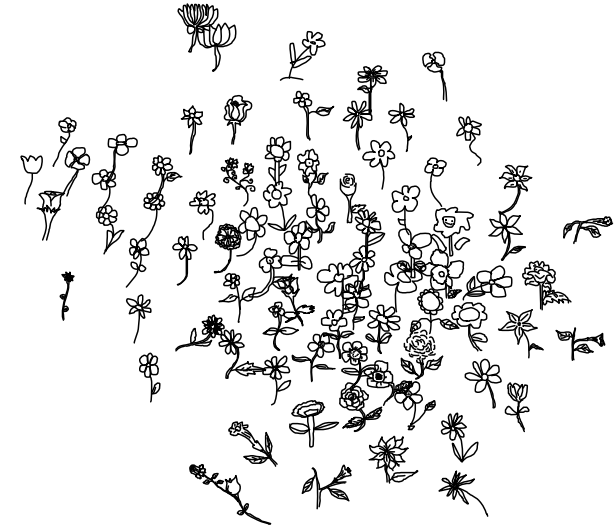
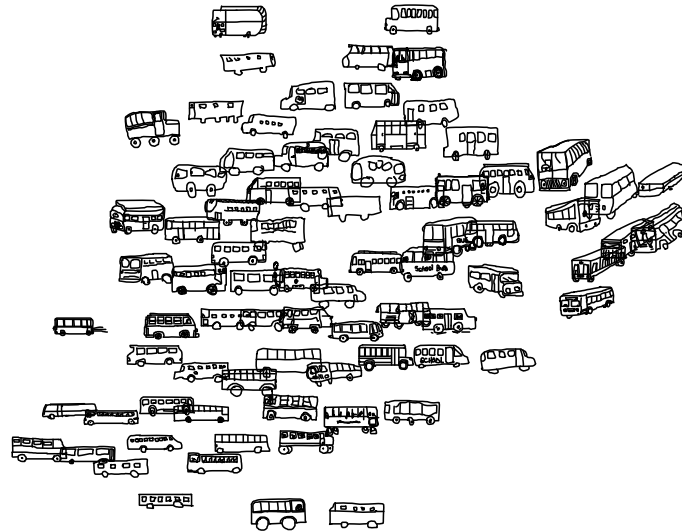
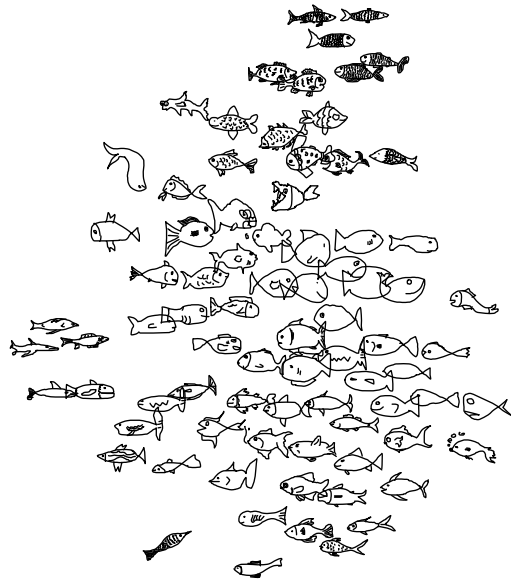


not easily recognizable



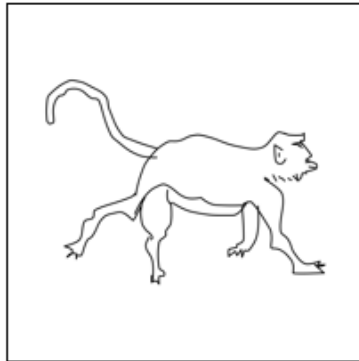
How do users sketch objects?

- 20,000 sketches in 250 categories
 - 1,350 unique participants, 741 hours drawing time



Human sketch recognition

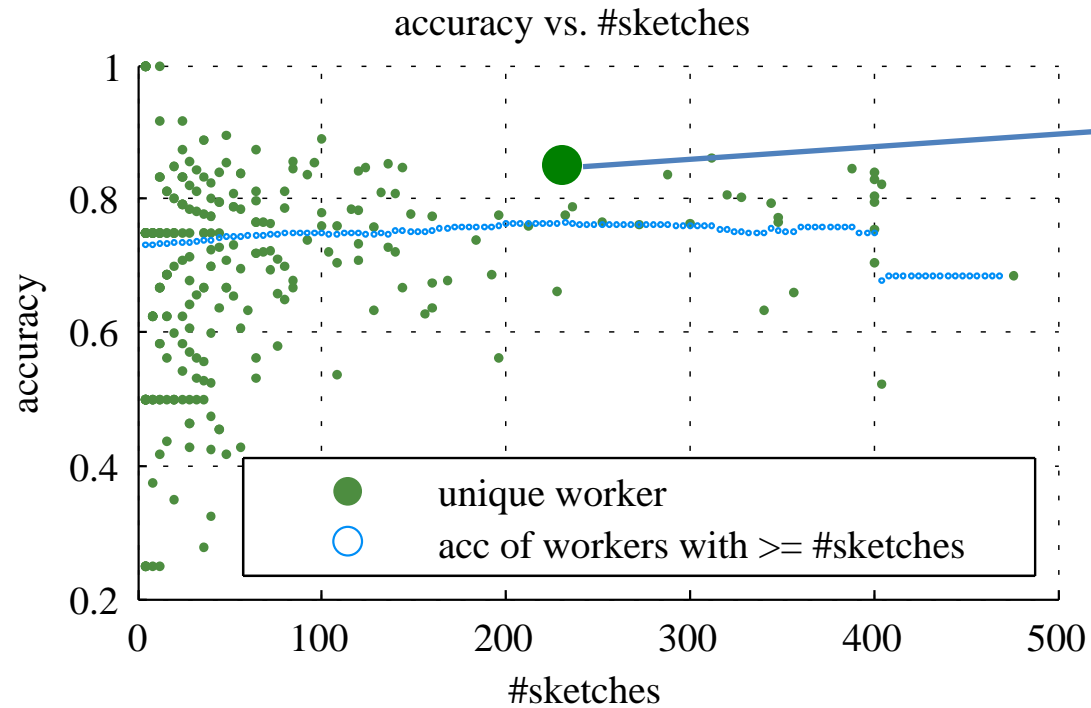
- 2nd study on Amazon Mechanical Turk



animals →	animal (air)	monkey ✓
buildings, home, office	animal (ground) a-l	mouse (animal)
leisure, personal items	animal (ground) m-z →	panda
nature, body, food	animal (water)	penguin
sound, figures, weapons		pig
vehicles, traffic		rabbit
		rooster
		scorpion
		sea turtle
		sheep
		snail
		snake
		spider
		squirrel
		standing bird
		teddy-bear
		tiger
		zebra

Human sketch recognition

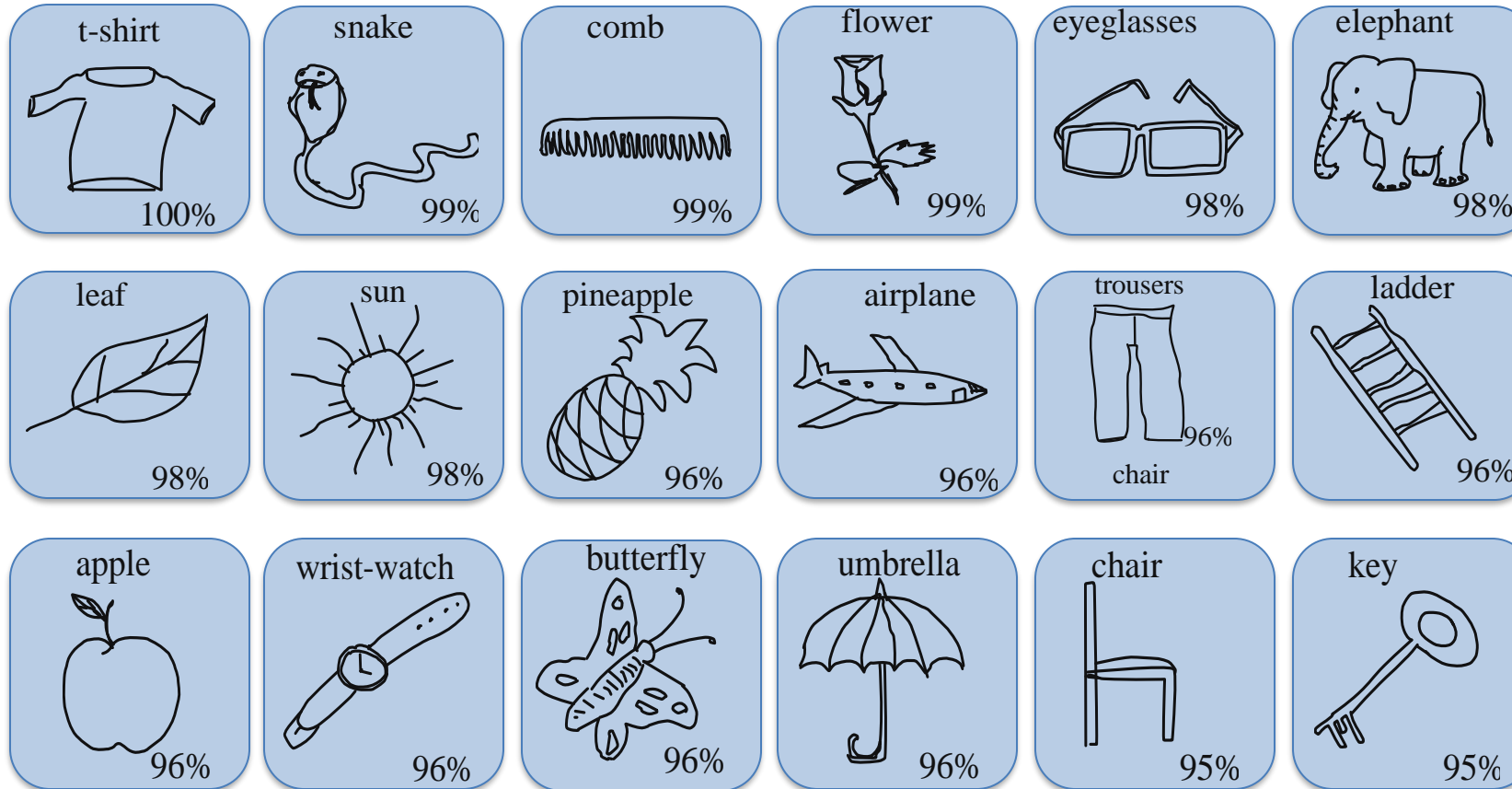
- 73% overall human recognition accuracy



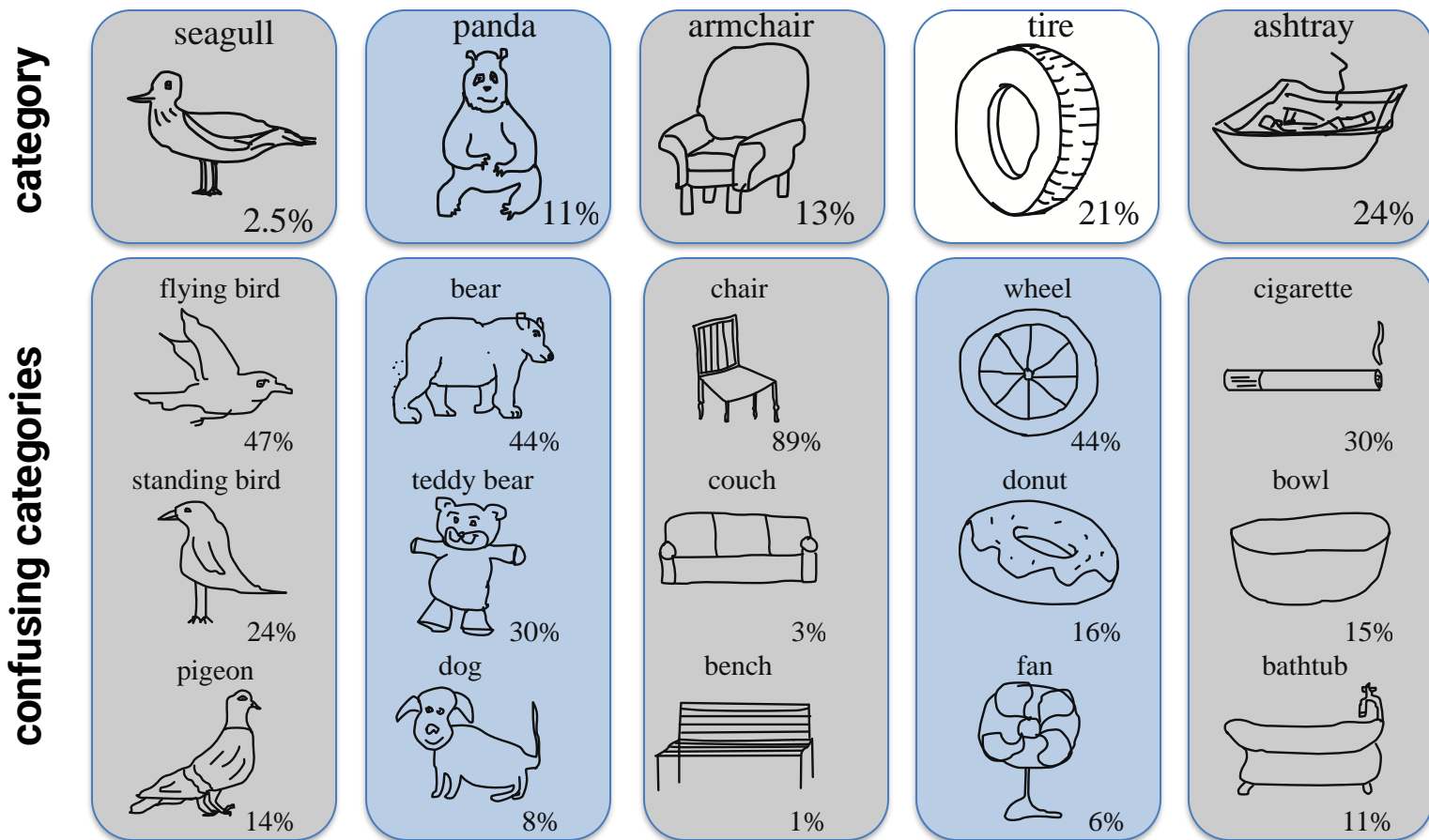
This particular worker:

- 250 sketches
- 85% accuracy

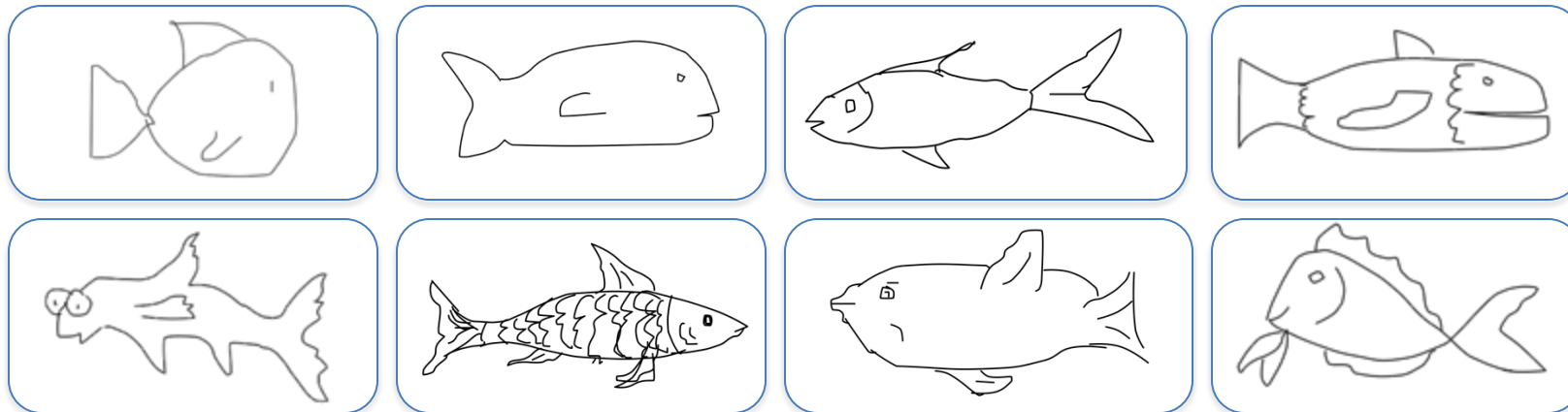
Human sketch recognition



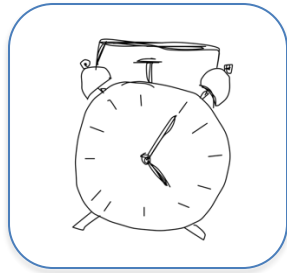
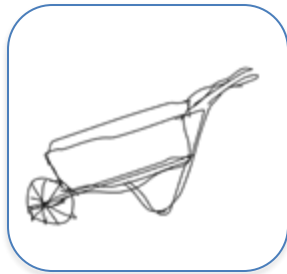
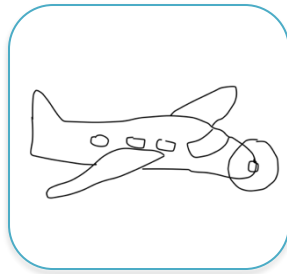
Human sketch recognition



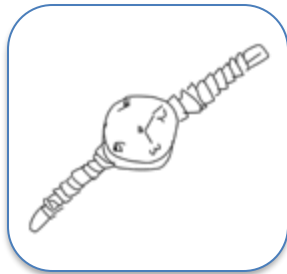
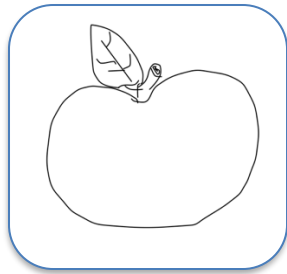
Computational sketch recognition



Computational sketch recognition



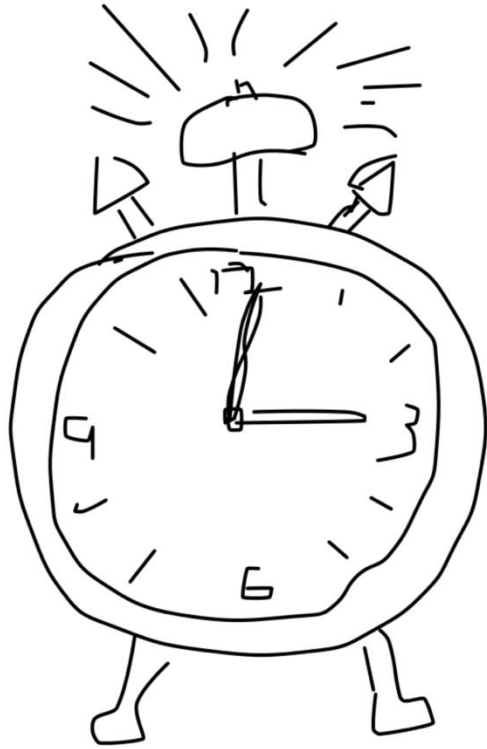
...



airplane
alarm clock
apple
:
wheelbarrow
wineglass
wristwatch

current system: 250 categories

Bag-of-feature representation



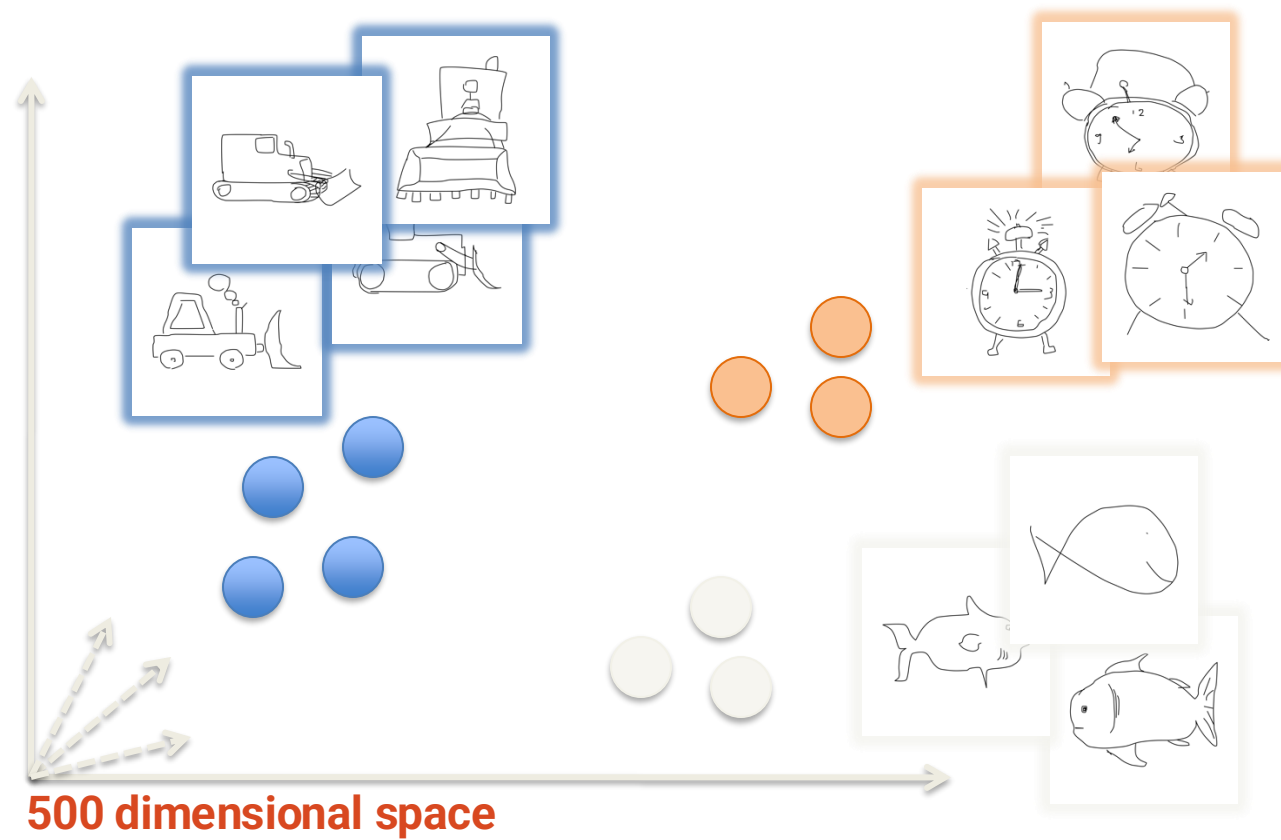
reduce into

feature vector

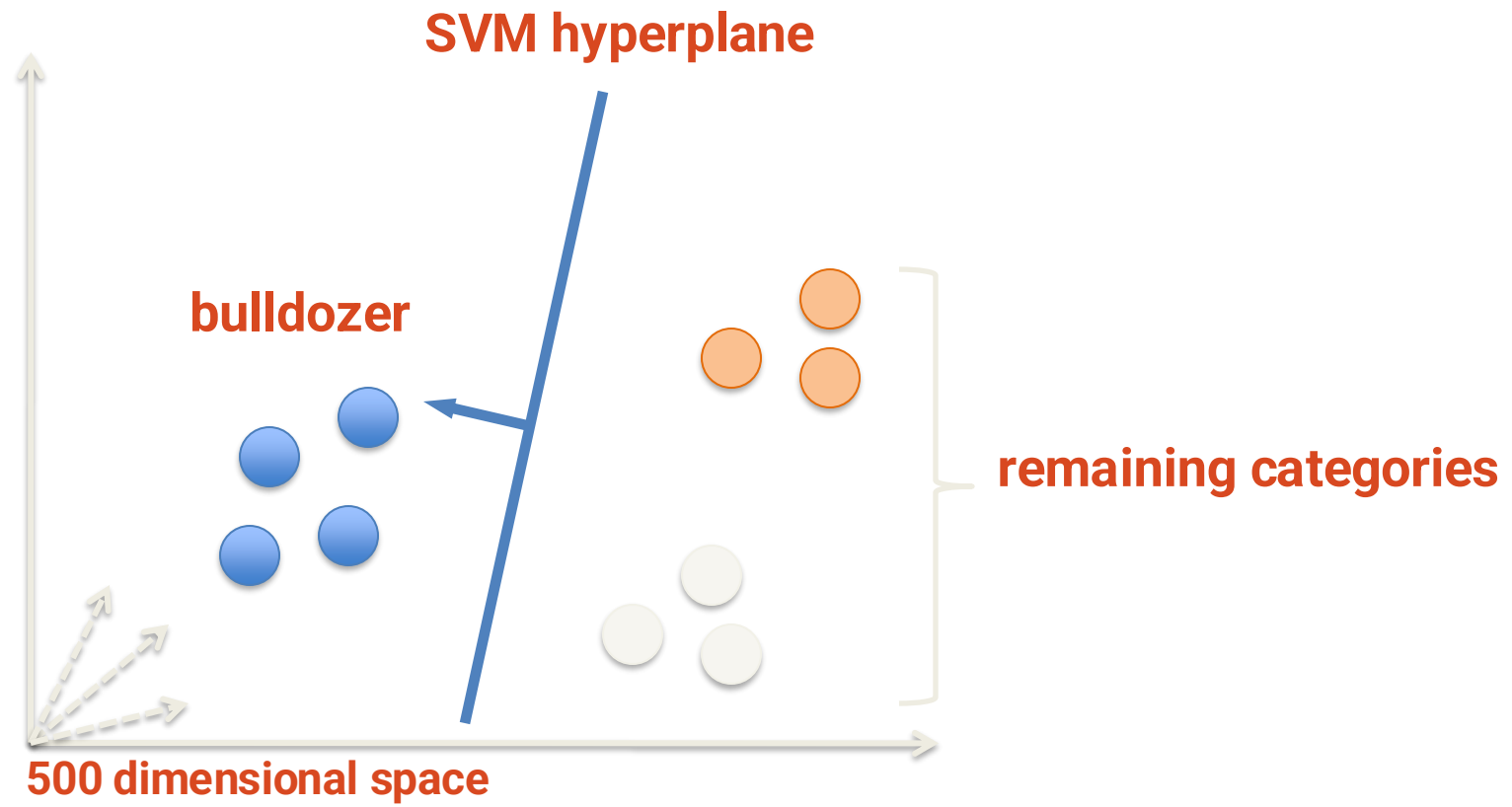


500 dimensional

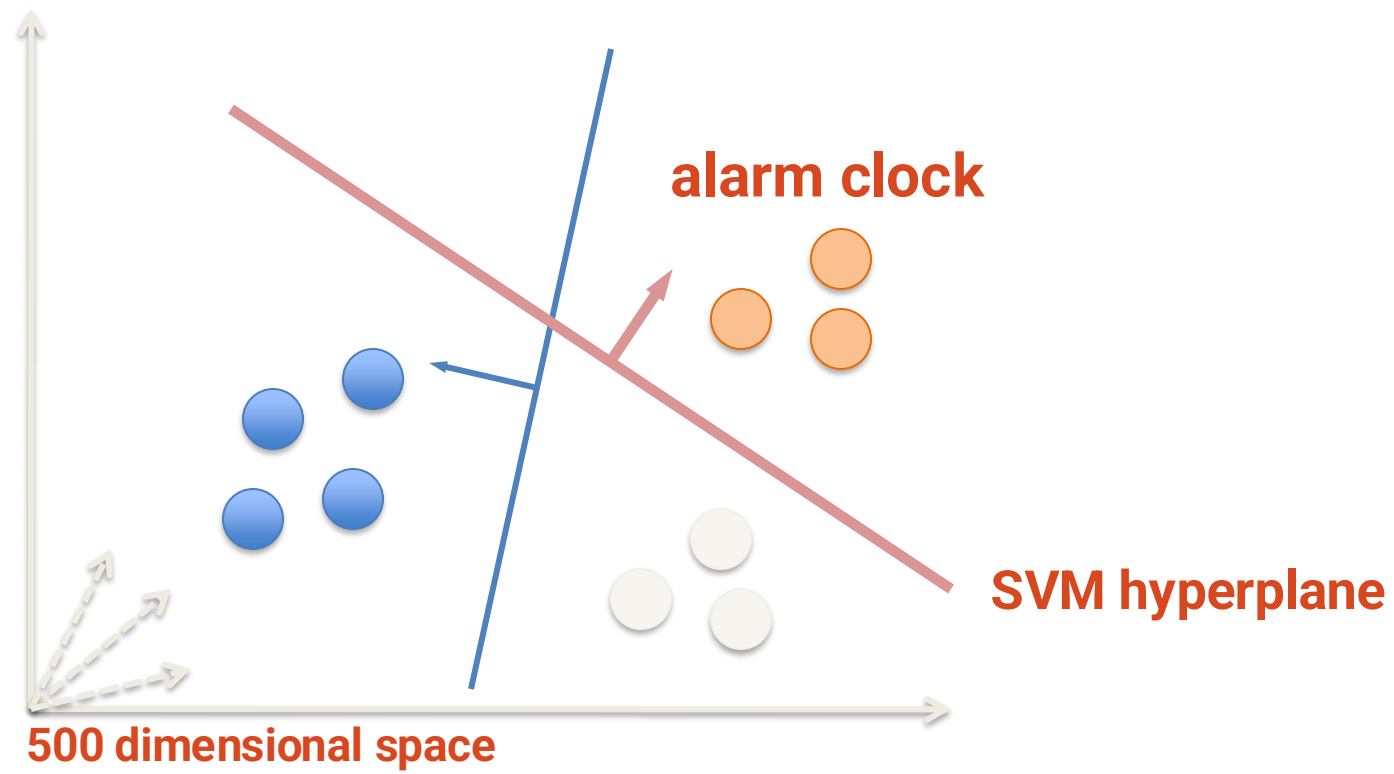
Sketch-feature space



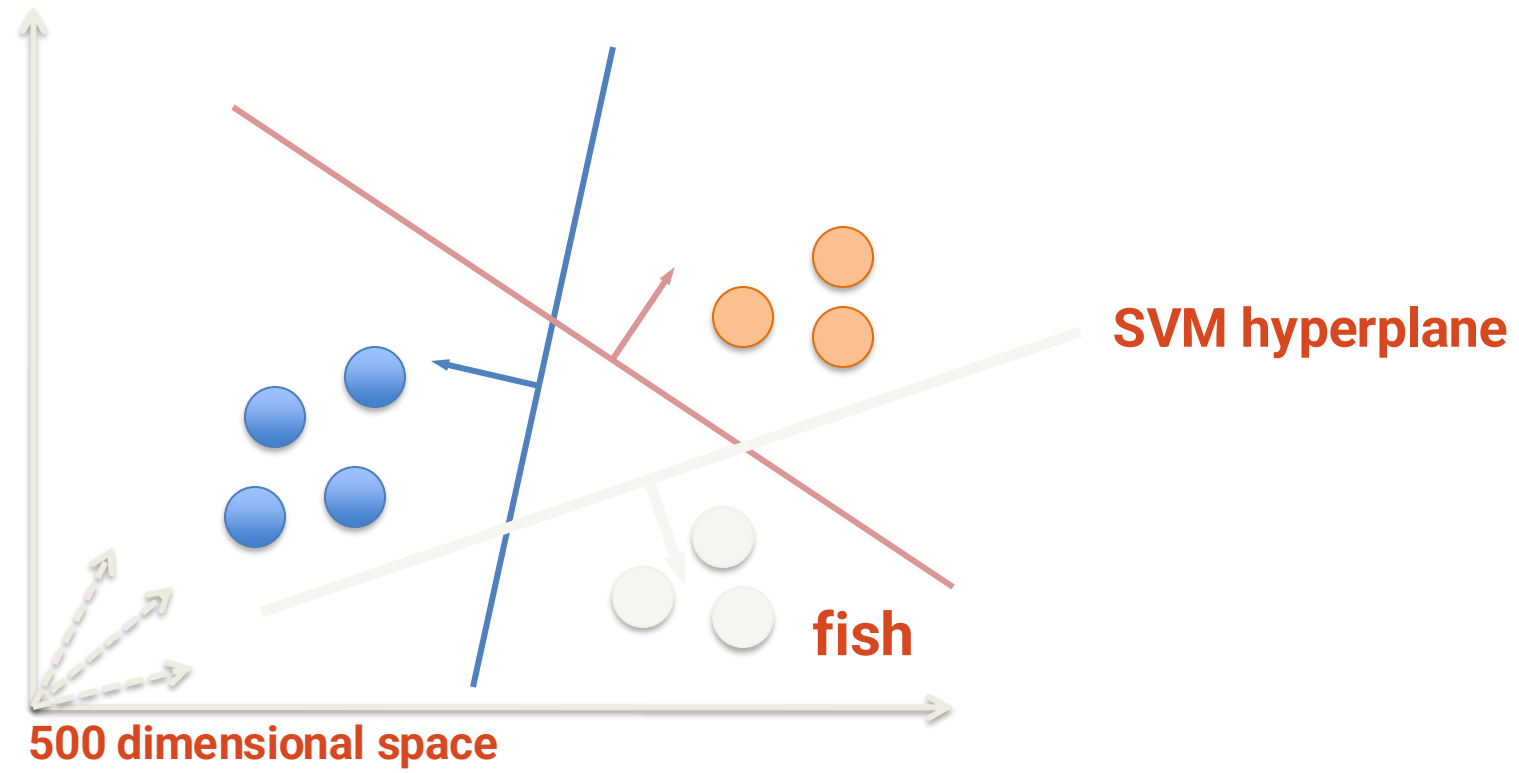
Training SVMs



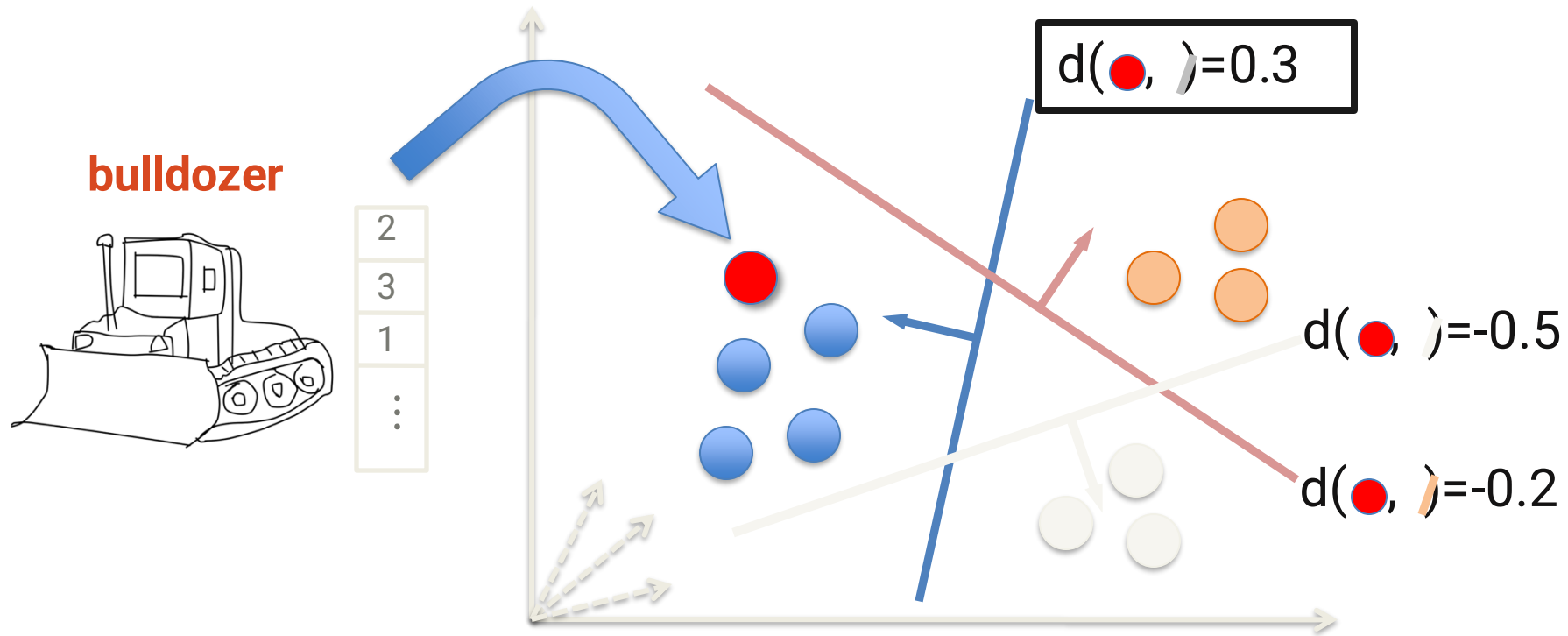
Training SVMs



Training SVMs



Classification

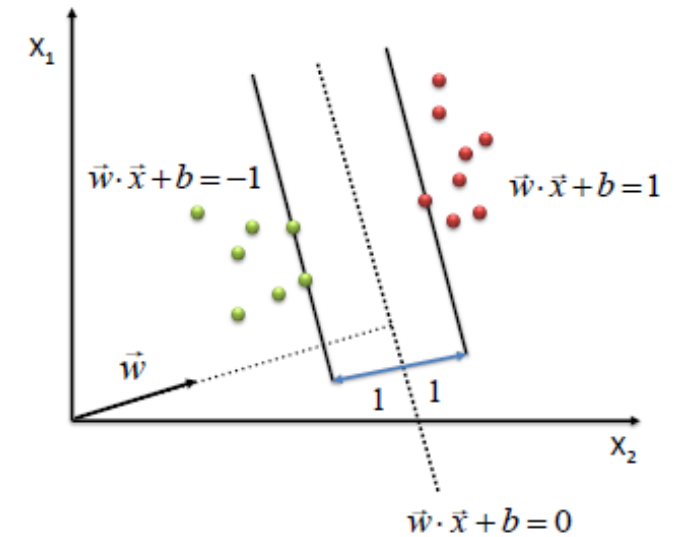
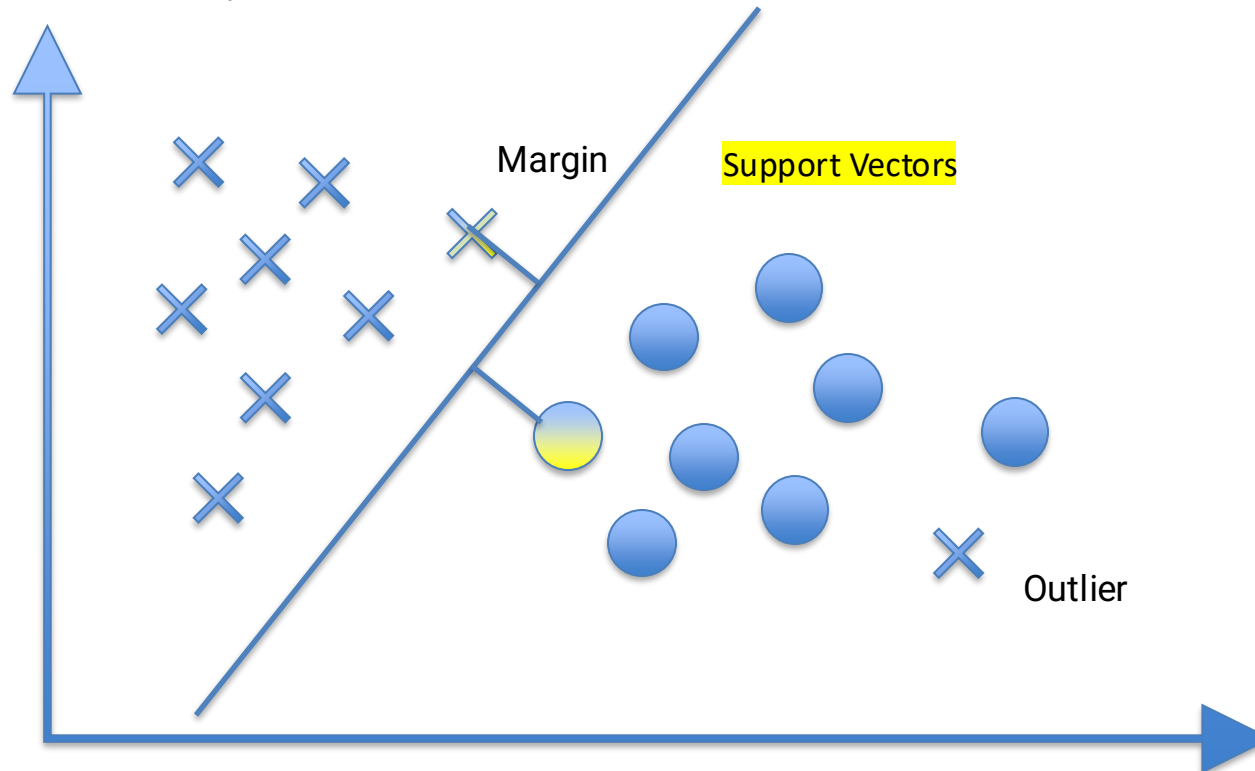


classify a sketch according to the model with largest response

Support Vector Machine

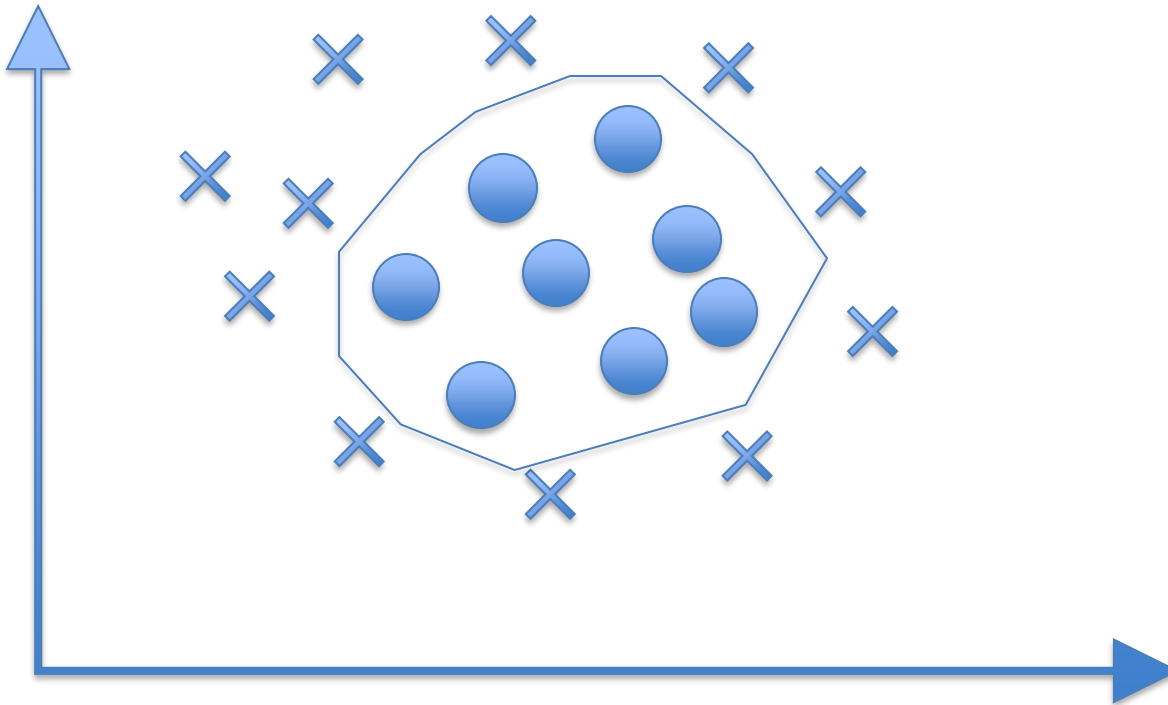
- Robust classifier
- maximises Margin and tolerates outliers

$$\text{minimize} \left(\frac{1}{2} \|w\|^2 + C \sum_{i=1}^n \max(0, 1 - y_i(w \cdot x_i + b)) + \lambda \|w\|^2 \right)$$



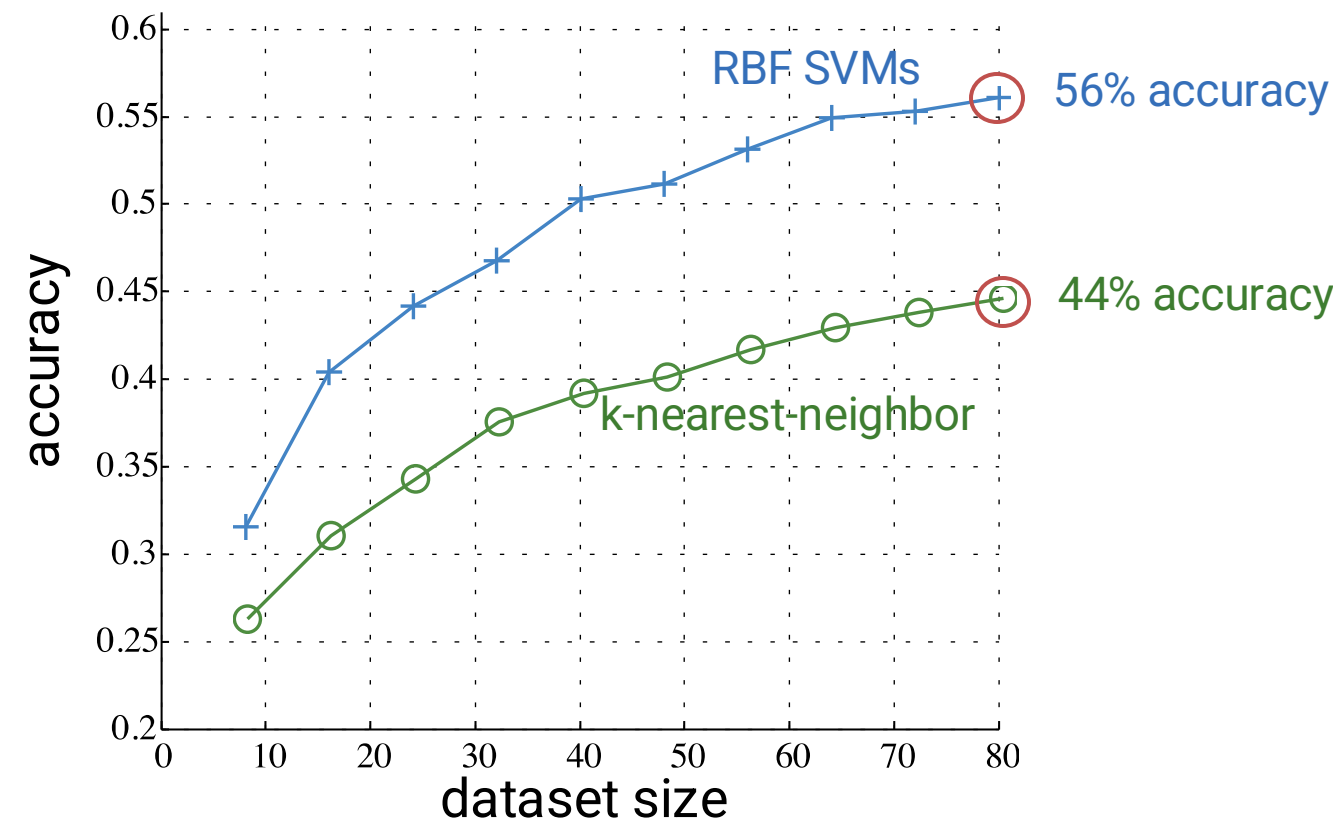
Non-linear Support Vector Machine

- non-linear separation by kernel trick
- Kernel function transforms low dimensional features into higher dimensional space
 - Separation can be found in higher dimensions
 - Non-linearity is achieved by back-transformation



White-board example, Code

Classification



Important!!! - Metrics for the evaluation of classification tasks

- **Accuracy:** Proportion of correctly classified examples

$$\text{Genauigkeit} = \frac{\text{Anzahl der korrekten Vorhersagen}}{\text{Gesamtanzahl der Beispiele}}$$

- **Precision:** Proportion of correct positive predictions out of all positive predictions

$$\text{Präzision} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Positives (FP)}}$$

- **Recall:** Proportion of correctly identified positive examples out of all actual positive examples

$$\text{Recall} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Negatives (FN)}}$$

Important!!! - Metrics for the evaluation of classification tasks

- **F1-Score:** harmonic mean of precision and recall

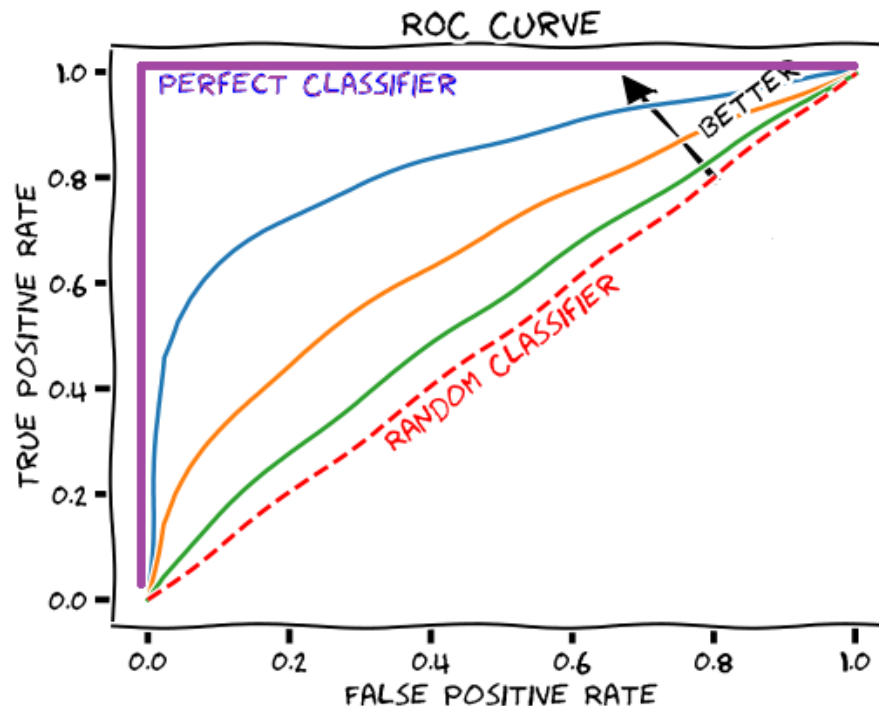
$$\text{F1-Score} = 2 \cdot \frac{\text{Präzision} \cdot \text{Recall}}{\text{Präzision} + \text{Recall}}$$

- **Confusion Matrix:** Table shows True Positives (TP), True Negatives (TN), False Positives (FP) and False Negatives (FN)

		True Class	
		Positive	Negative
Predicated Class	Positive	TP	FP
	Negative	FN	TN

Important!!! - Metrics for the evaluation of classification tasks

- **AUC-ROC (Area Under the Receiver Operating Characteristic Curve):**
Grafische Darstellung eines Klassifikationsmodells bei verschiedenen Schwellenwerten.
 - AUC (Area Under the Curve) misst gesamte zweidimensionale Fläche unter der ROC-Kurve
 - AUC von 1 repräsentiert ein perfektes Modell, AUC von 0.5 Modell nicht besser als Zufall



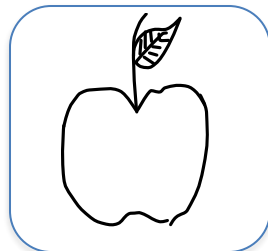
Computational Sketch recognition

human:
computer:

easy

96%

96%



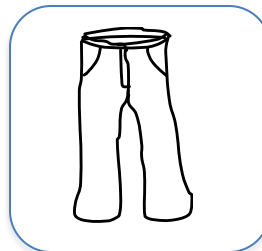
100%

96%



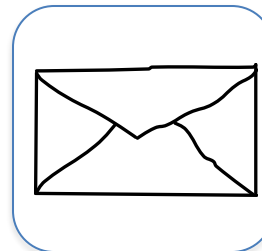
96%

96%



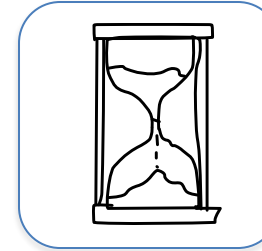
95%

96%



73%

96%

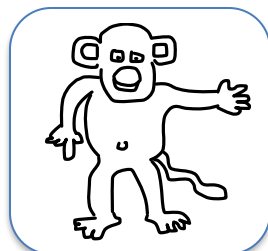


human:
computer:

difficult

79%

7%



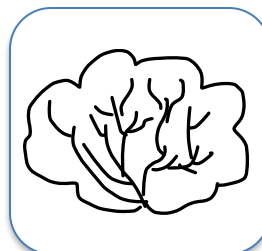
81%

7%



35%

11%



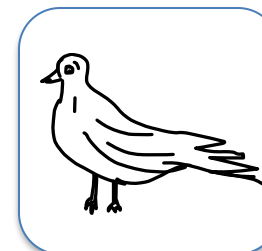
51%

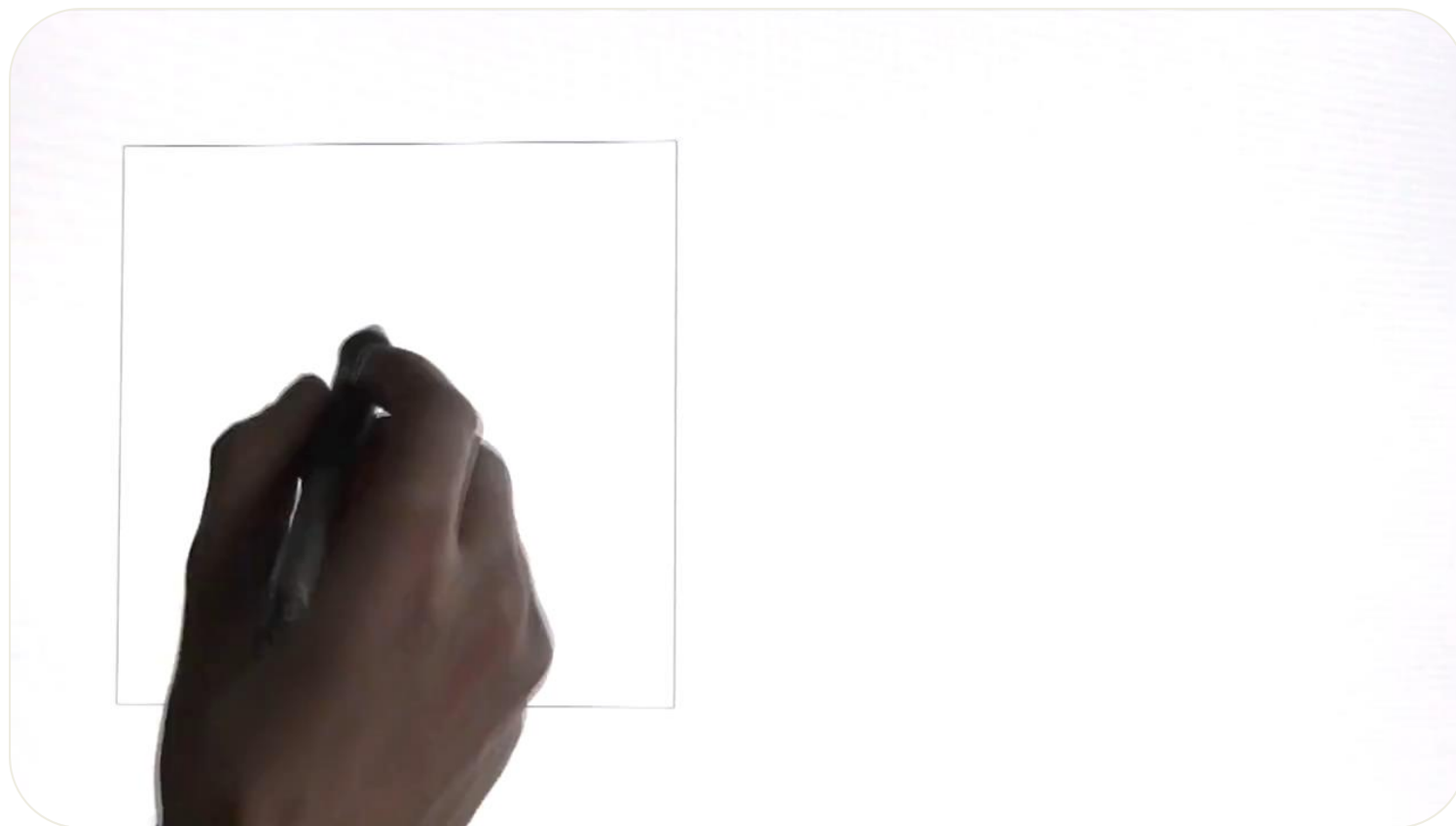
11%

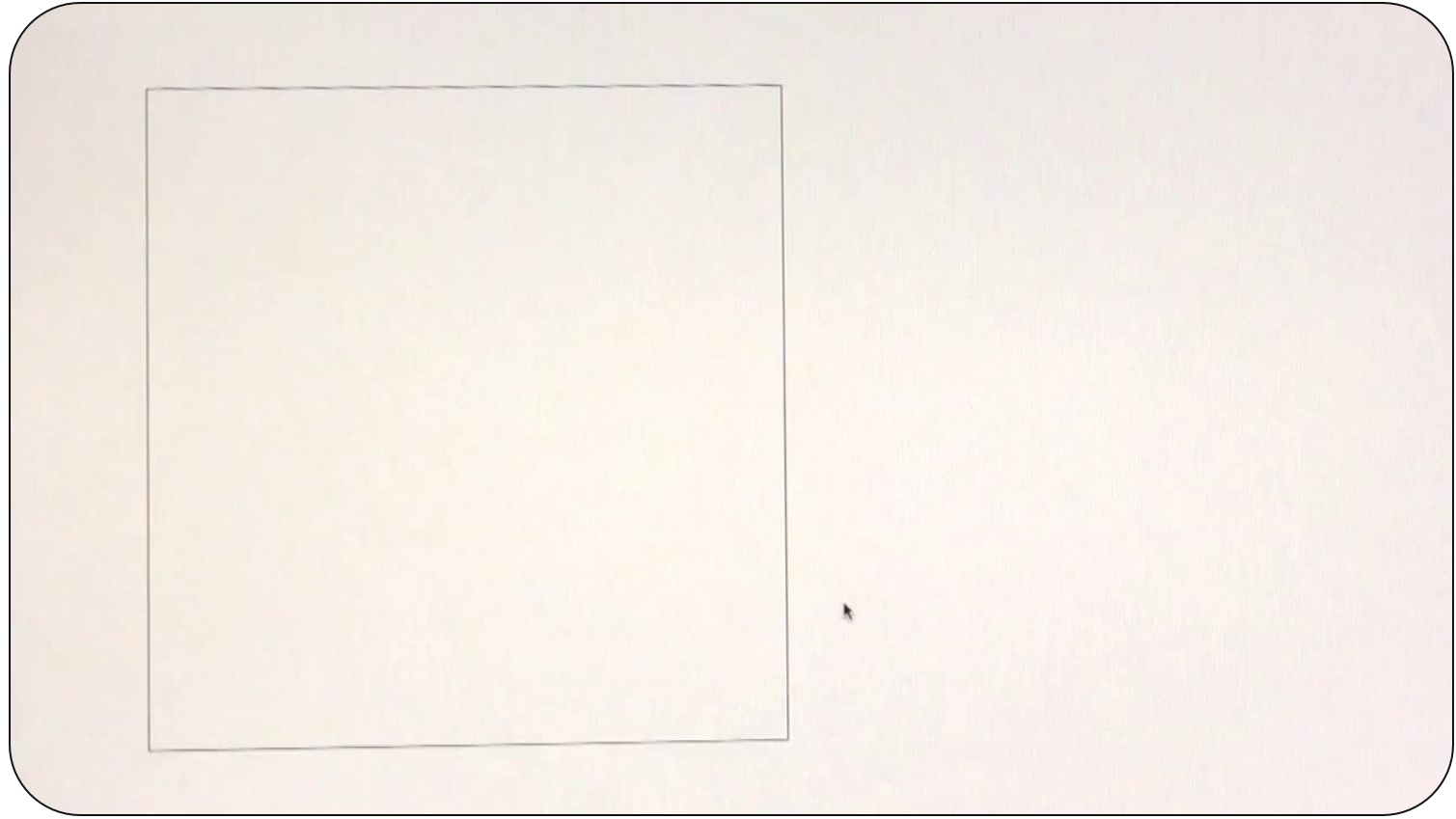


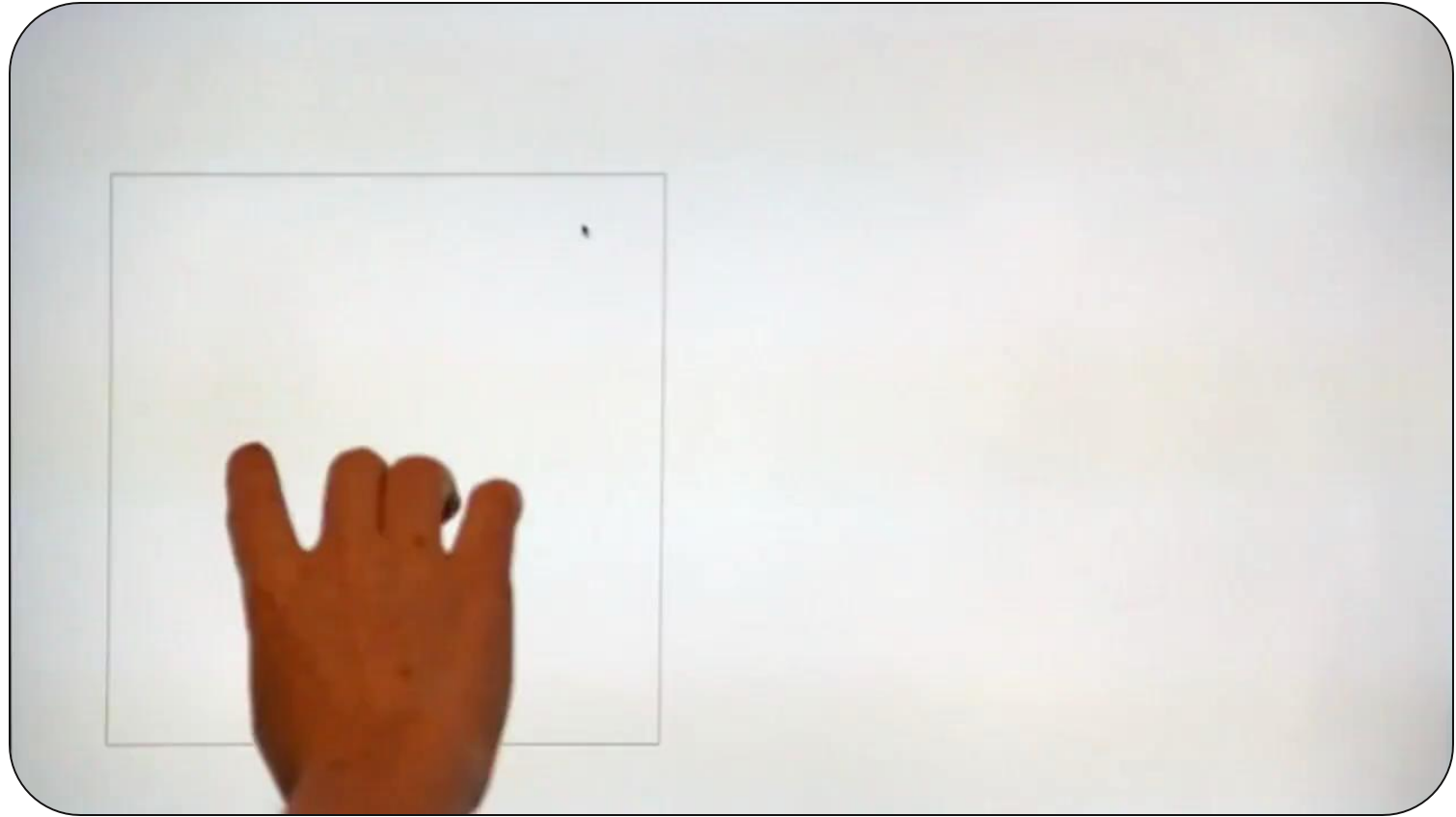
31%

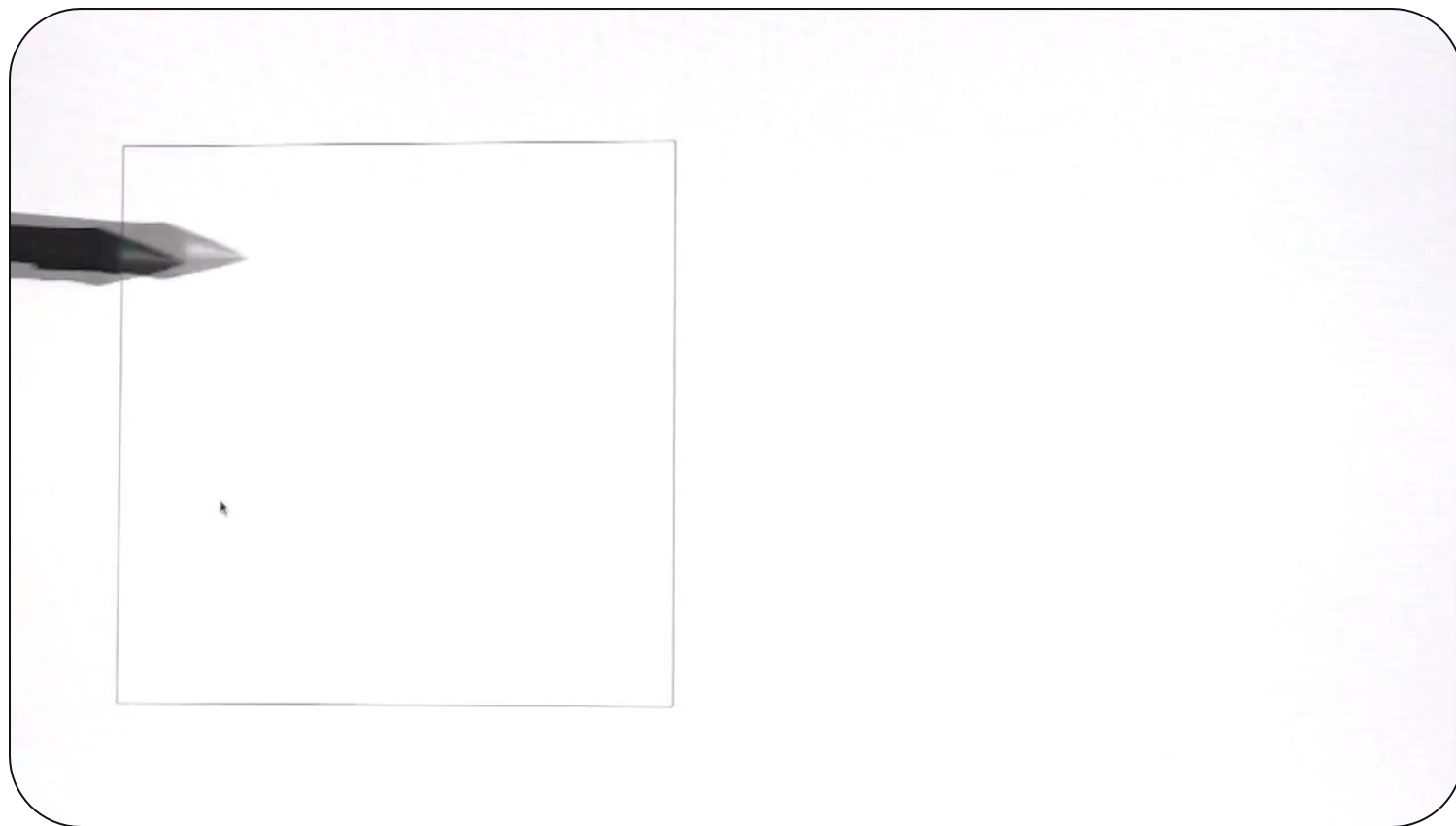
14%



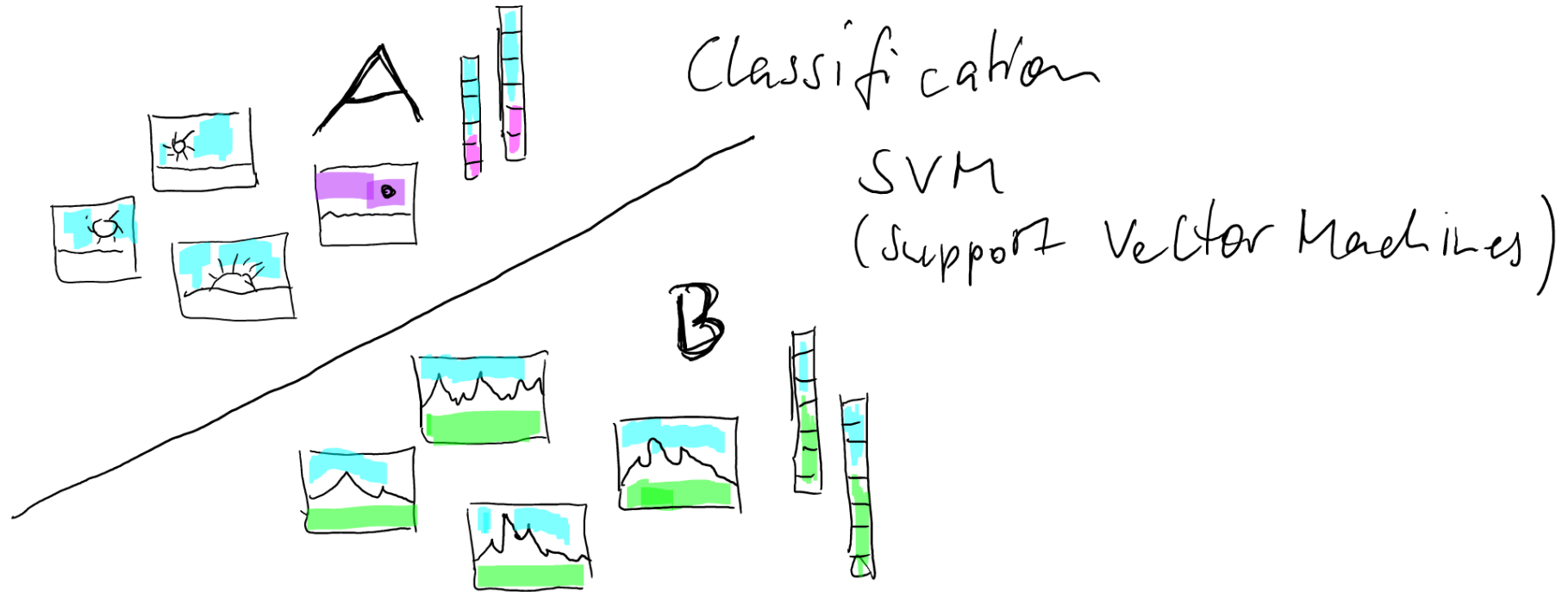








Support Vector Machines



Code a short demo

What if?

We could train a ***neural network*** to create image features that we can easily match.

*Krizhevsky, A., Sutskever, I., Hinton, G.E.: Imagenet classification with deep convolutional neural networks.
In: Neural Information Processing Systems (2012)*

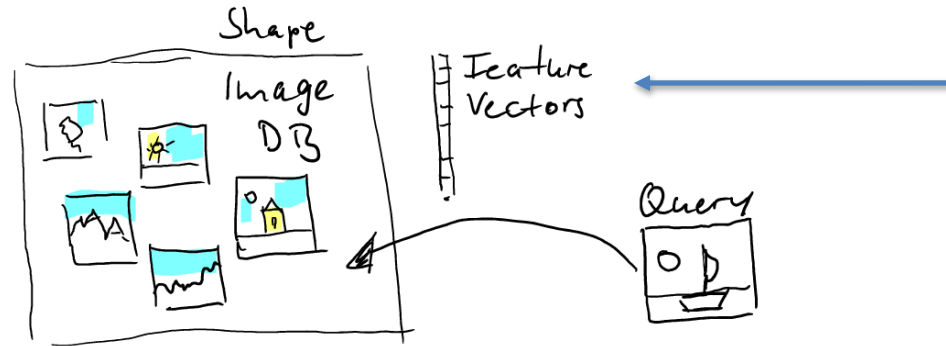
Draw me something

and I'll tell you, what I think it is!

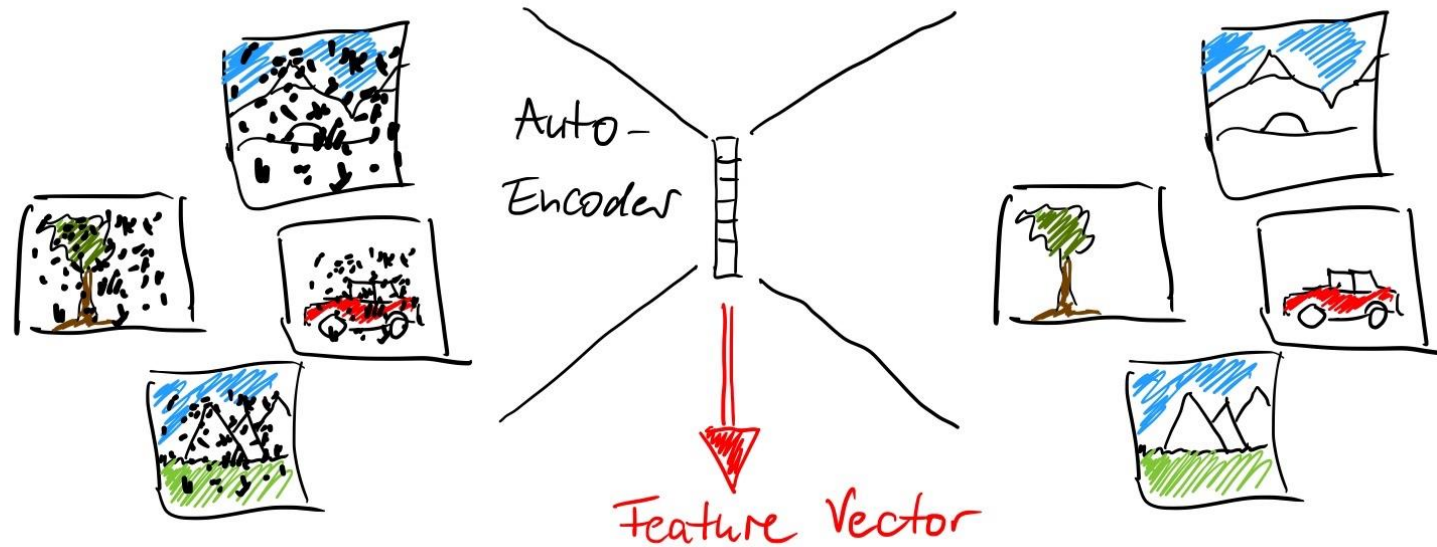


Start again!

Content-based Image Retrieval using Convolutional Neural Networks



Same idea BUT:
Can we learn features?



Neural network introduction

- Watch all four videos!

https://www.youtube.com/playlist?list=PLZHQOb0WTQDNU6R1_67000Dx_ZCJB-3pi