

# Introduction to Machine Learning

## Lecture 6: Conclusion

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# Outline

This lecture includes:

- ▶ A **model selection** lab
- ▶ A few aspects of machine learning we have not mentioned
  - ▶ **Feature engineering**
  - ▶ **Dimensionality reduction**
- ▶ Feedback and final Q&A

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In case there are too many samples, a simple solution is to apply subsampling, e.g. just take into account 10% of the samples.

- ▶ Recall the mini-batch  $k$ -means
- ▶ Be careful with the **class balance**
  - ▶ Imbalanced classes: **subsample the majority class**
  - ▶ Little to no imbalance: **Stratified sampling**

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It is also important to use common sense and expert knowledge when possible:

- ▶ Some variables might be intuitively meaningless to solve the ML problem
- ▶ ML often aims at mimicking/automatic a human logic



# Dimensionality reduction with PCA

PCA = Principal Component Analysis

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Rough idea:

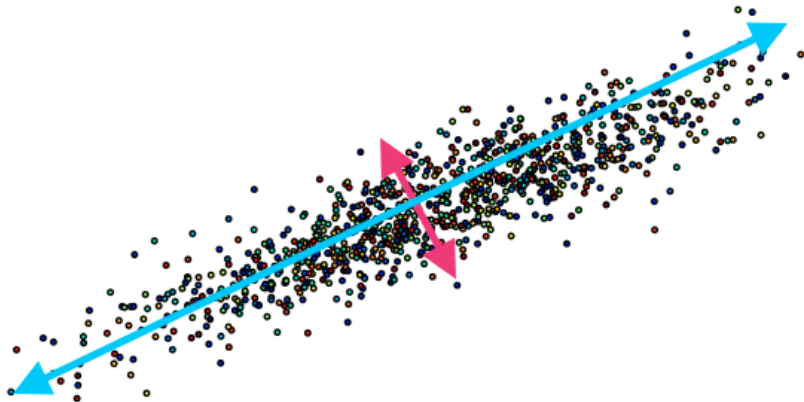
- ▶ Find high variance axes
- ▶ Select the  $k$  axes with the highest variances
- ▶ Project the data on these axes

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Feature engineering is often **data-dependent**: You won't use the same features from text data and from images or videos.

# Feature engineering in text analysis

There are several challenges when dealing with text data:

- ▶ Mining text can lead to a huge amount of data to process
- ▶ Not all the data is relevant
- ▶ Texts can be of different size
- ▶ ...



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Hence, there is **a need to preprocess** it before giving it to any ML algorithm.

## Feature engineering in text analysis with TF-IDF

Given terms  $t \in T$  and documents  $d \in D$ , we can define:

$\text{TF}(t, d)$  = Frequency of term  $t$  in the document  $d$

$$\text{IDF}(t, D) = \log \left( \frac{|D|}{|\{d \in D, t \in d\}|} \right)$$

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a	2
sample	1

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Exercise: Cf. Board

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Exercise: Cf. Board Note: We can go further, e.g. with  $n$ -grams.

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**SIFT is patented** and cannot be used in all situations: There exist alternatives based on the same idea such as SURF (Speeded-Up Robust Features)

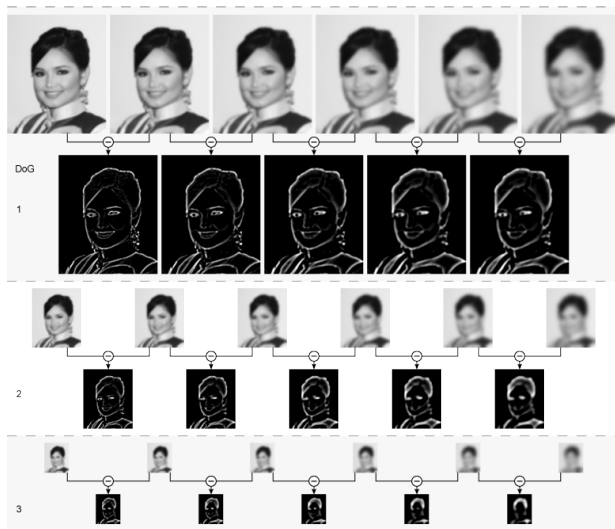


# SIFT algorithm

Key steps:

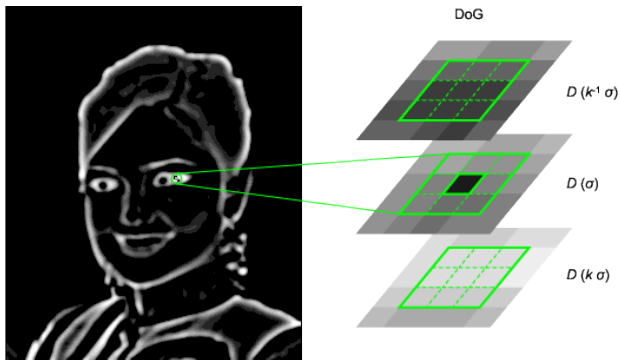
- ▶ Detect extrema at different scale by difference of gaussians
- ▶ Detect interest points in the image
- ▶ Assign orientations to create SIFT features

# SIFT: Difference of Gaussians (DoG)



# SIFT: Extrema detection

Interest points are among the local extrema in the  $3 \times 3 \times 3$  neighborhood:



## SIFT: Extrema detection

Post-processing:

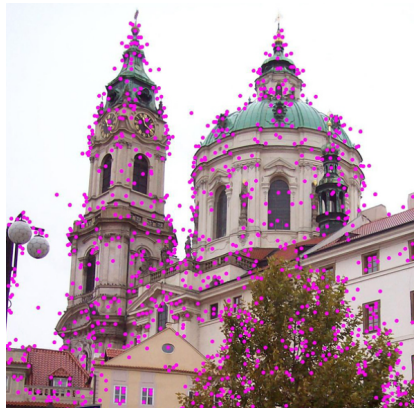
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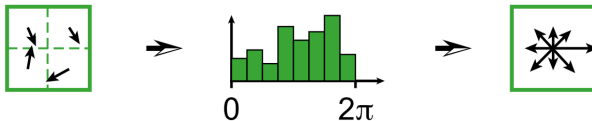
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Before/after:

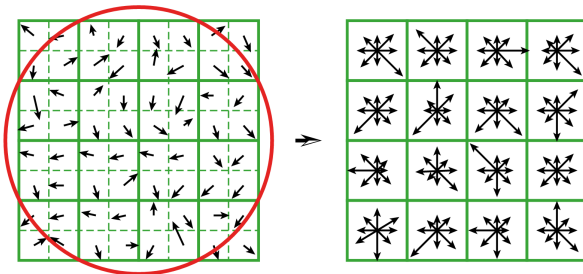


## SIFT: Orientation assignment

For each interest point, compute the orientation histogram:



Do it for a neighborhood of the interest point:



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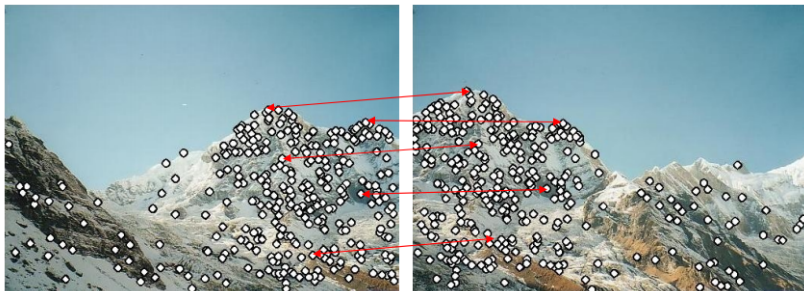
YouTube video example



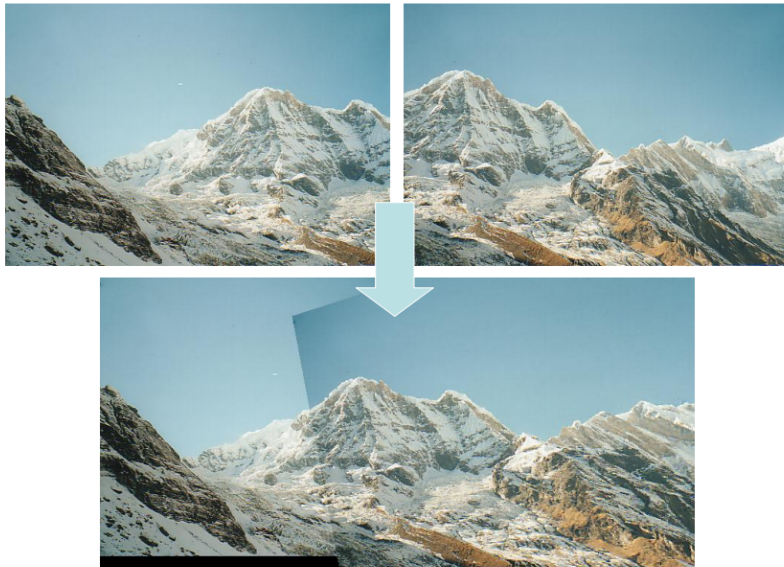
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## SIFT illustration: Panorama



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There are plenty of libraries and examples available online... Don't hesitate to play with it!

Thank you! Questions?  
Any feedback?