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

Dimensionality reduction

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Hence, there is a need to pre-process the data.

Dimensionality reduction

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
-

Dimensionality reduction with PCA

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Rough idea:

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- Select the k axes with the highest variances
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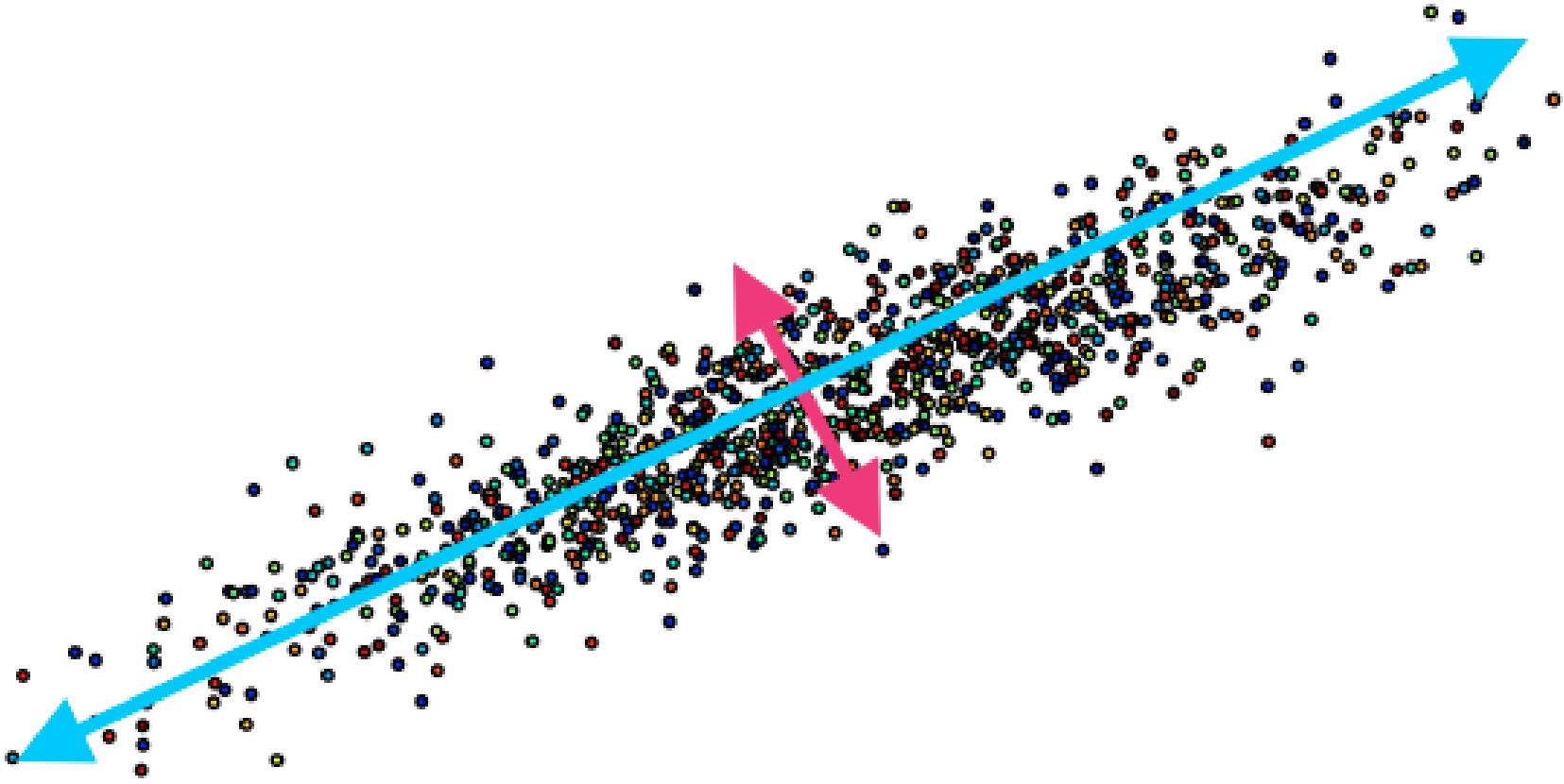

Feature engineering

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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: TF-IDF

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 analysis in image processing

In images, we often want to detect interest points such as **edges** and **corners**.

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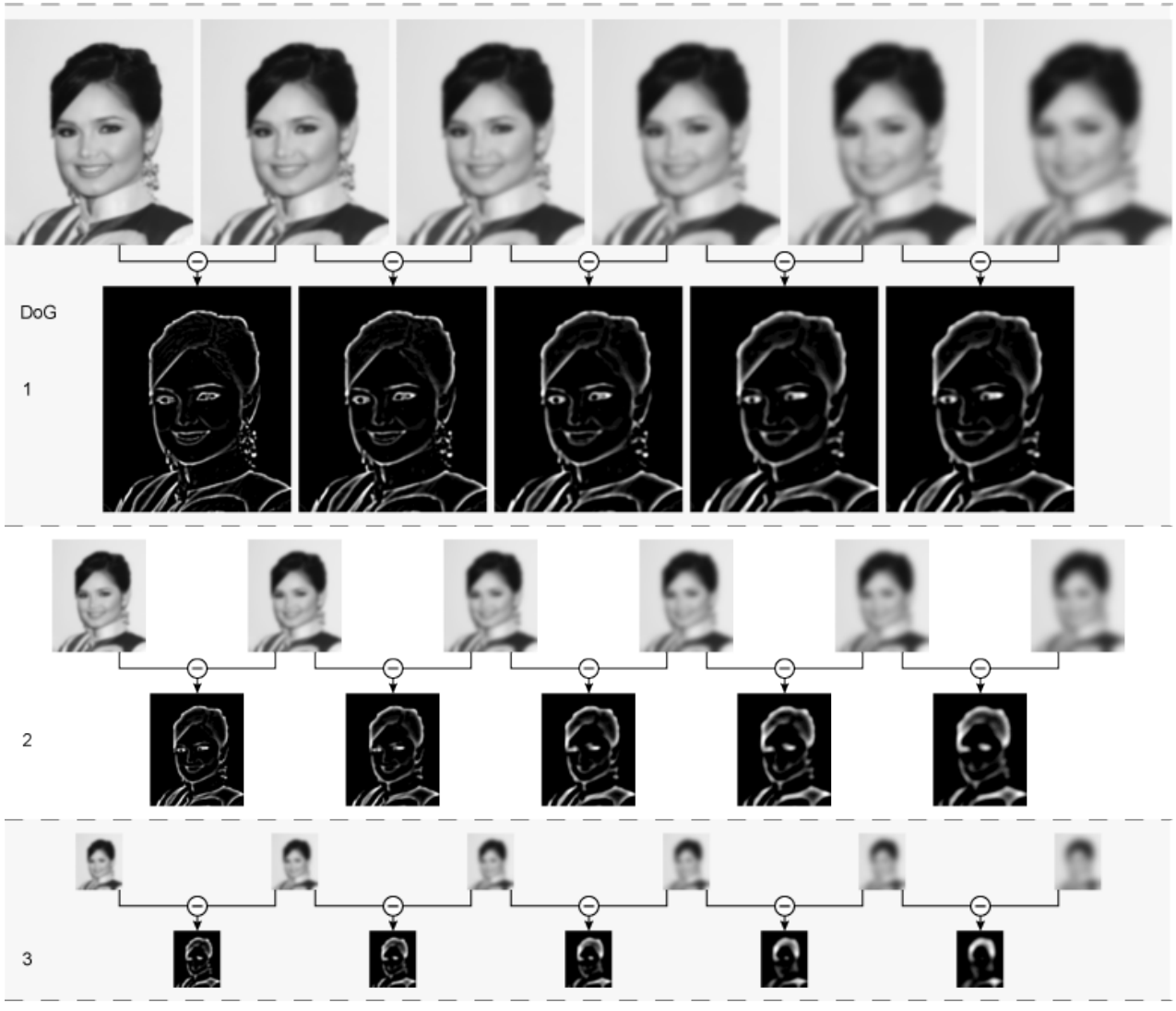
SIFT is patented and cannot be used in all situations: There exist alternatives based on the same idea such as SURF (Speeded-Up Robust Features)

SIFT algorithm

Key steps:

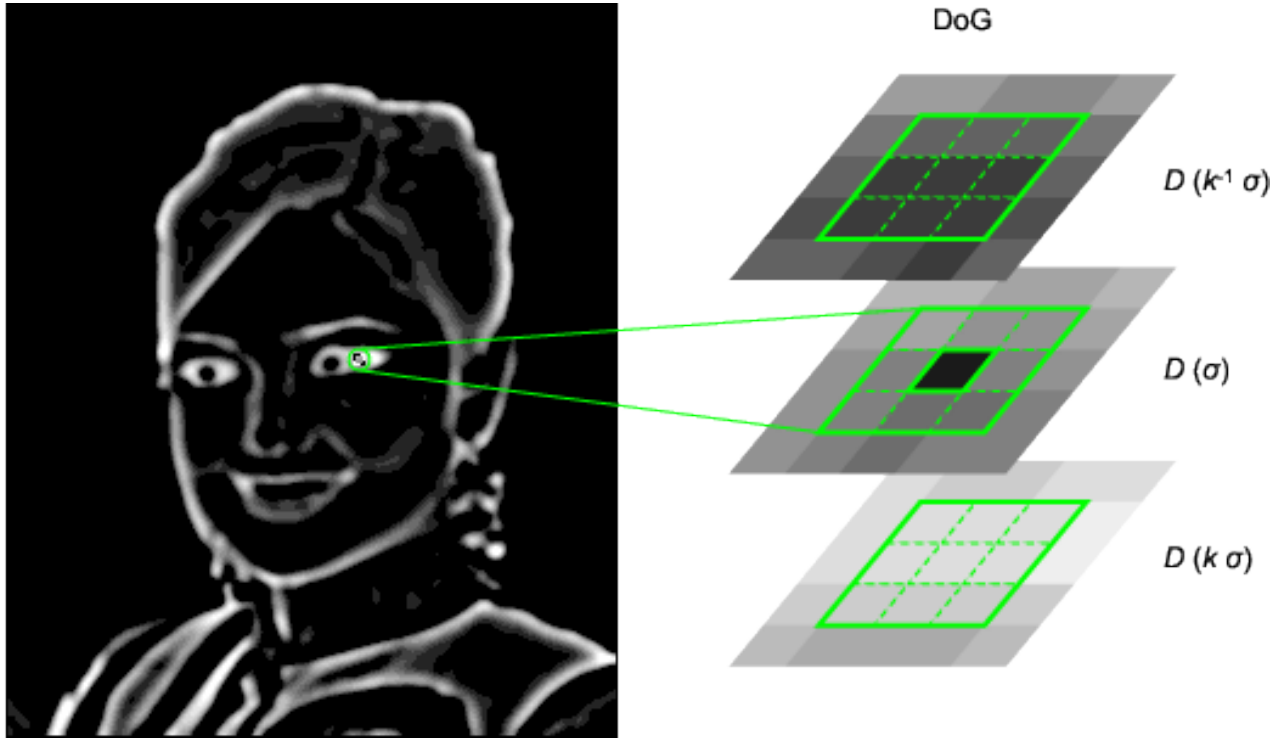
- Detect extrema at different scale by difference of gaussians
- Detect interest points in the image
- Assign orientations to create SIFT features

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:

- Remove low-contrast points
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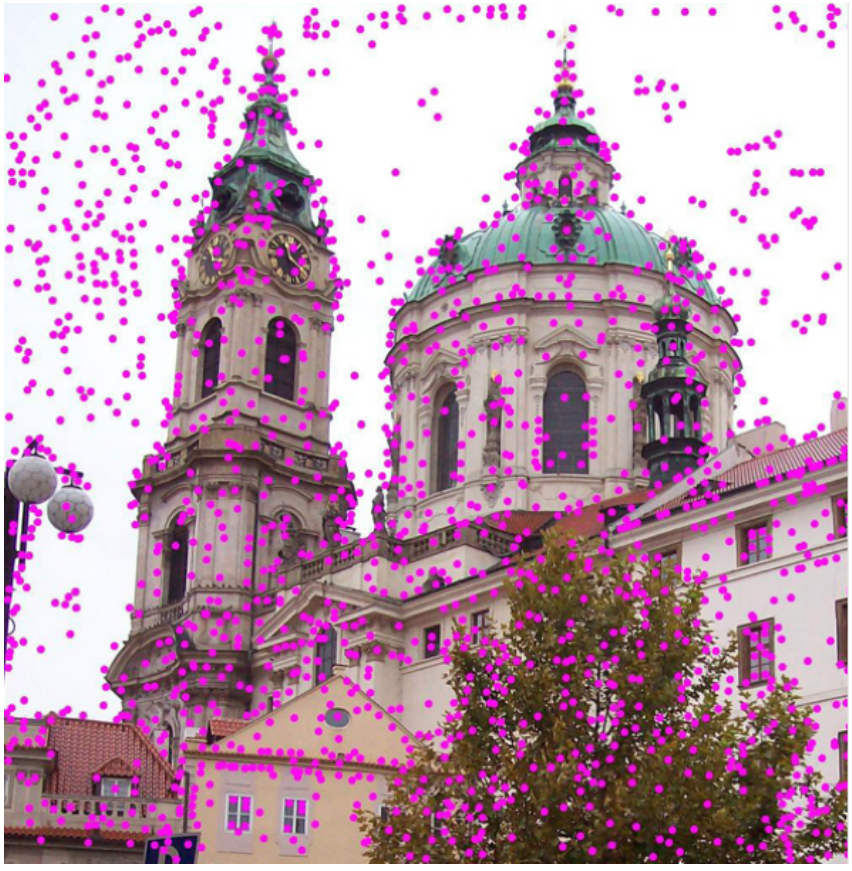
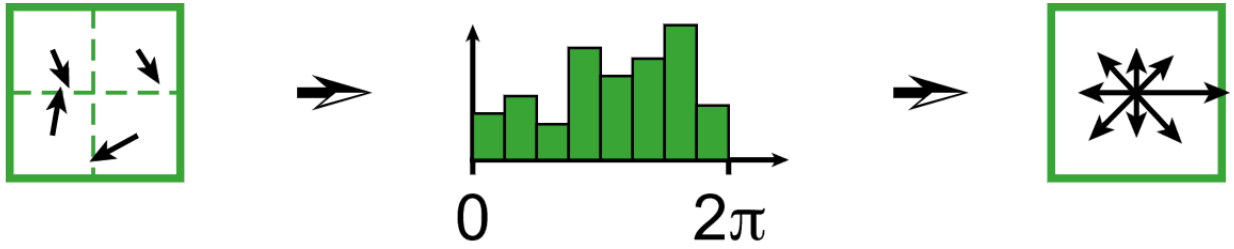
Before/after:

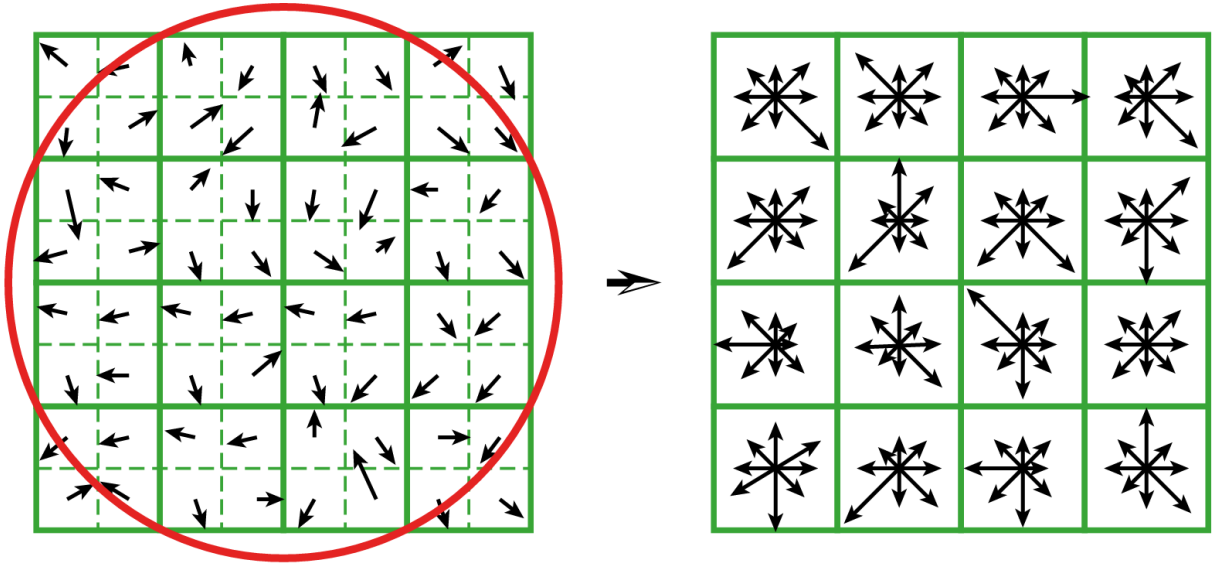


SIFT: Orientation assignment

For each interest point, compute the orientation histogram:



Do it for a neighborhood of the interest point:



SIFT applications

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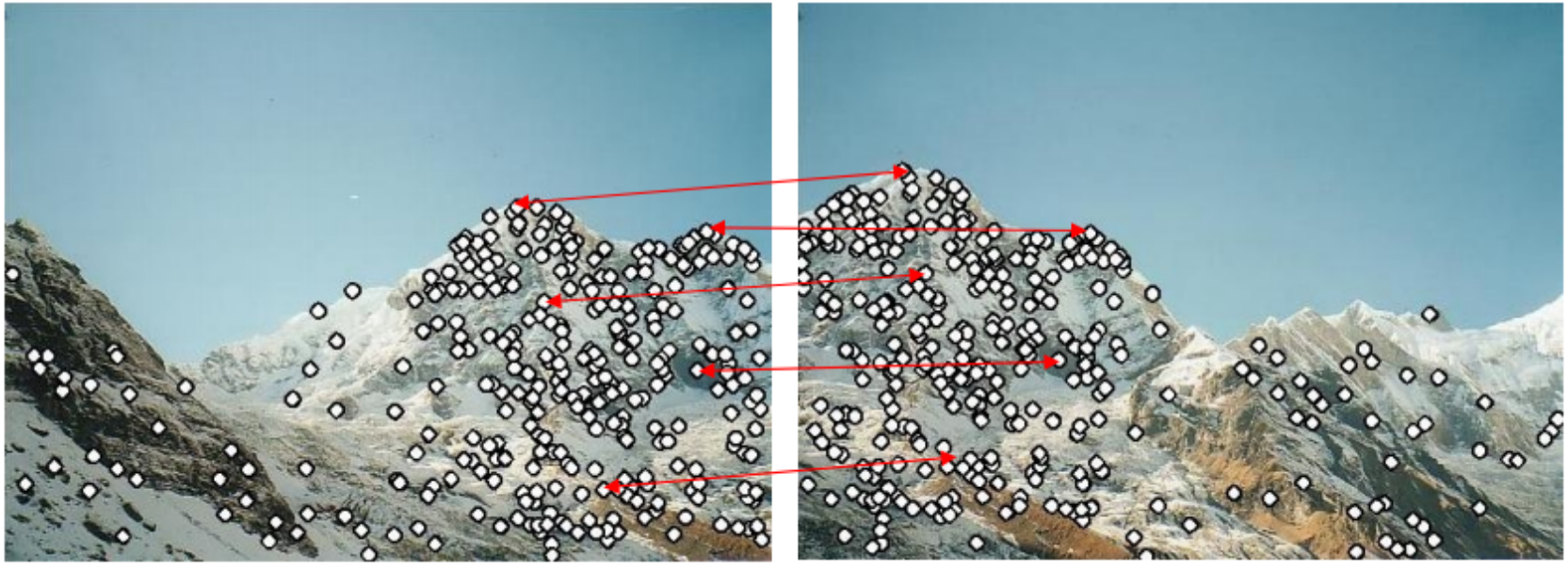
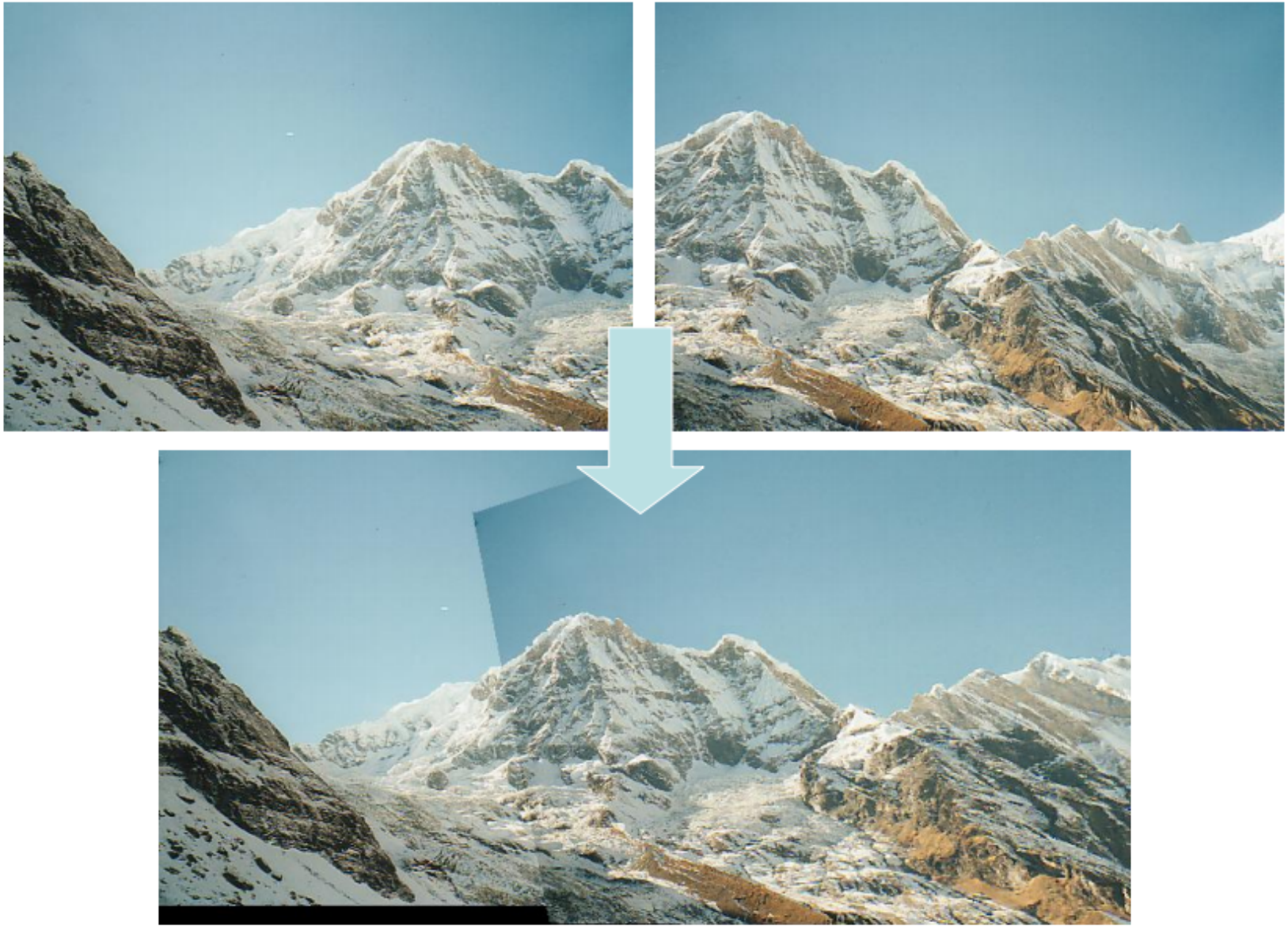


SIFT illustration: Panorama



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There's **no general-purpose solution** (at least for now): It is important to **look at the data** and **adapt to the situation**.

Thank you! Questions?
Any feedback?