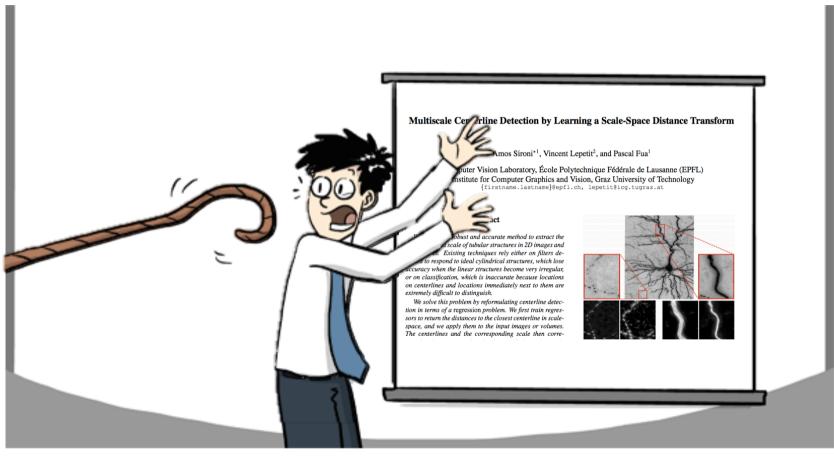
### How to Give a Good Talk

Vincent Lepetit



#### A talk is *not* a paper presented in oral form



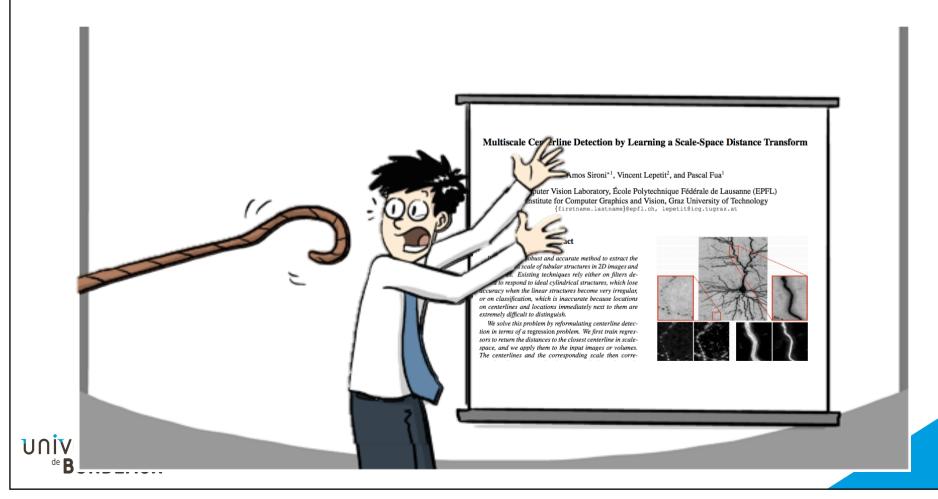




A talk is *not* a paper presented in oral form.

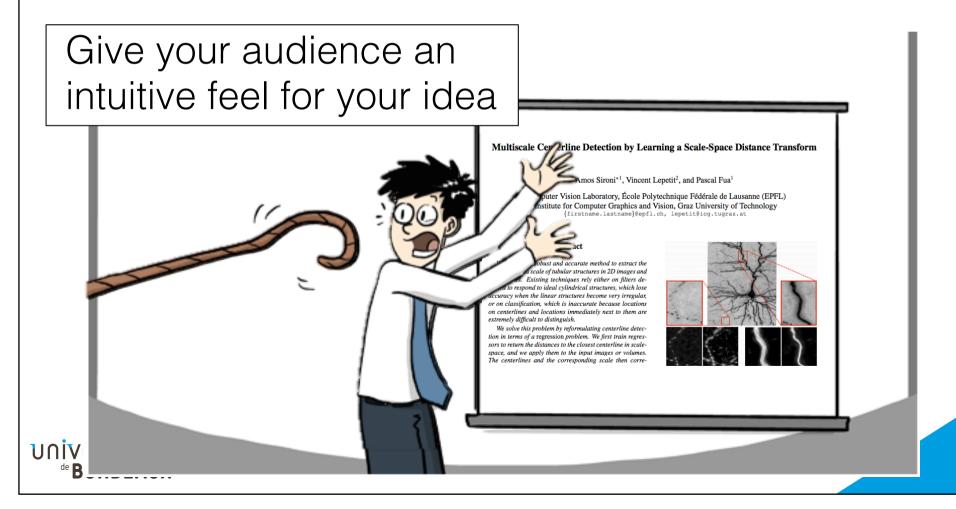
A talk is mostly an *advertisement* for the paper:

Make the audience understand your conclusion and the intuition behind your method, not the technical details.



A talk is *not* "a paper presented in oral form".

A talk is mostly an *advertisement* for the paper: Make the audience understand your conclusion and the intuition behind your method, not the technical details.



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A talk is mostly an *advertisement* for the paper: Make the audience understand your conclusion and the intuition behind your method, not the technical details.



### About the Style

- Make sure the text is easy to read: example;
- Avoid a blank background, but don't use an overloaded template;
- Show the slide number;
- Use sans-serif fonts (Arial, Calibri, Helvetica Light, not Times);
- Font size at least 24pt (this is 28pt).





Put yourself in the shoes of a person that knows nothing about your work.

### Tell a story:





#### You have only a few minutes to get people interested

What is the problem you are aiming to solve?

Why is it interesting to solve it?

Why is it difficult to solve it?

about 20% of the talk

Motivation Contribution, results, comparison



### Start with some results!

What is the problem you are aiming to solve?

Why is it interesting to solve it?

Why is it difficult to solve it?

about 20% of the talk

Motivation Contribution, results, comparison



### Scalable Recognition with a Vocabulary Tree (2006)

David Nistér, Henrik Stewénius

### Query Images for the Web





#### Visually similar images





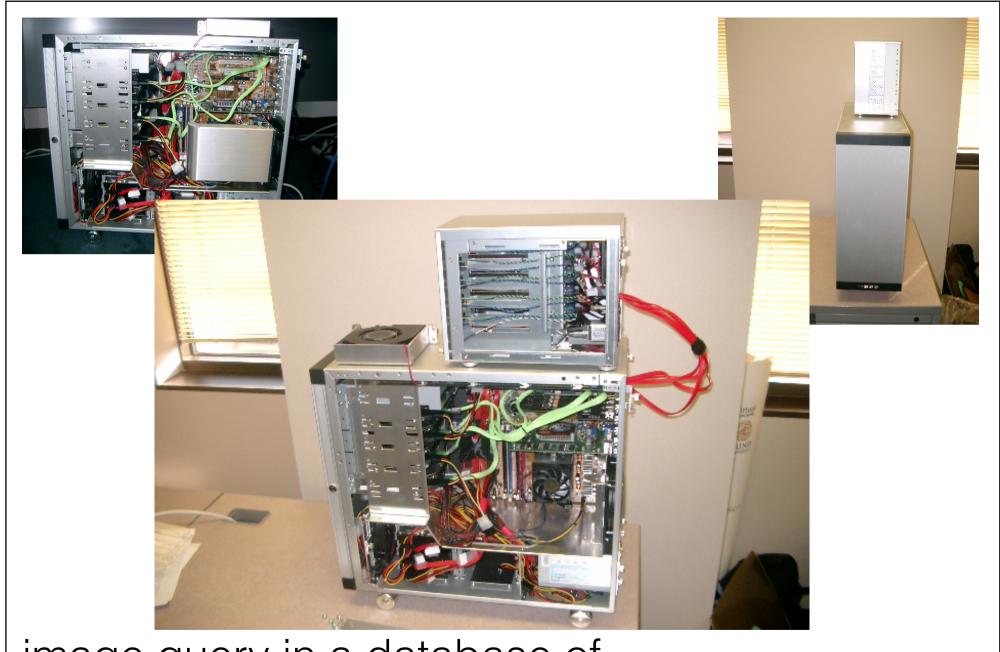
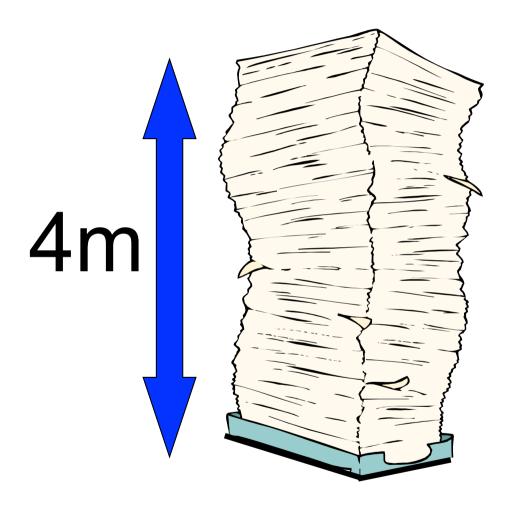


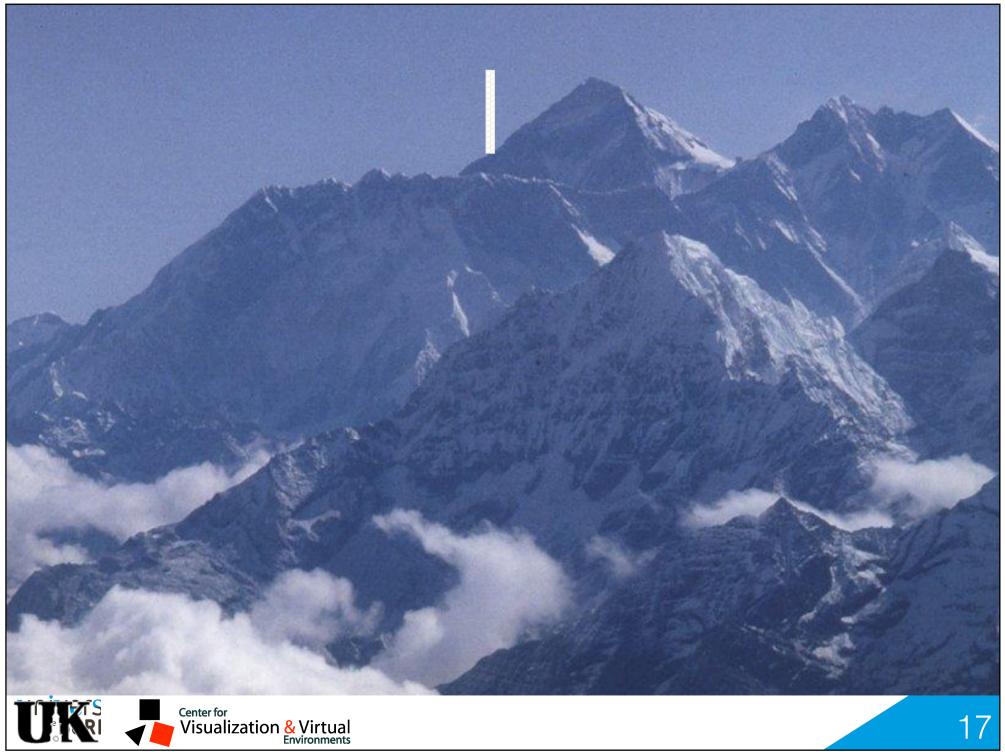
image query in a database of 110,000,000 images in 5.8 Seconds

### 50 Thousand Images









#### Start with some results!

What is the problem you are aiming to solve?

Why is it interesting to solve it?

Why is it difficult to solve it?

If your results are convincing, the audience will listen to your talk

comparison



### Related Work?

Can be useful to show that:

- the problem is important if there are many related papers;
- the problem is new if there is very few references.

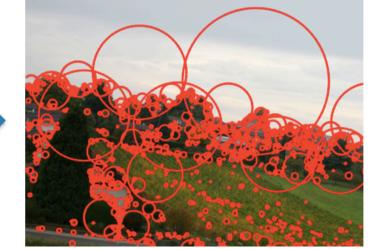
 But don't spend too much time on the related work, your talk is about your work.



## Feature Point Pipeline



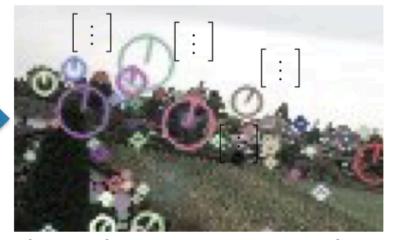
input image



feature point detection



orientation estimation



descriptor computation

- Harris, C., Stephens, M., "A Combined Corner and Edge Detector," AVC, 1988
- Mikolajczyk, K., Schmid, C., "Scale and Affine Invariant Interest Point Detectors," IJCV, 2004
- Förstner, W., Dickscheid, T., Schindler, F., "Detecting Interpretable and Accurate Scale-Invariant Keypoints," ICCV, 2009
- Rosten, E., Porter, R., Drummond, T., "Faster and Better: A Machine Learning Approach to Corner Detection." TPAMI, 2010
- Zitnick, C., Ramnath, K., "Edge Foci Interest Points", ICCV, 2011
- Mainali, P., Lafruit, G., Tack, K., Van Gool, L., Lauwereins, R., "Derivative-Based Scale Invariant Image Feature Detector with Error Resilience", TPAMI, 2014

• ...











- · Winder, S., Brown, M., "Learning Local Image Descriptors," CVPR, 2007
- Tola, E., Lepetit, V., Fua, P., "A Fast Local Descriptor for Dense Matching," CVPR, 2008
- Fan, B., Wu, F., Hu., Z., "Aggregating Gradient Distributions into Intensity Orders: A Novel Local Image Descriptor," CVPR, 2011
- Alahi, A., Ortiz, R., Vandergheynst, P., "FREAK: Fast Retina Keypoint," CVPR, 2012
- Simonyan, K., Vedaldi, A., Zisserman, A., "Learning Local Feature Descriptors Using Convex Optimisation," TPAMI, 2014
- Zagoruyko, S., Komodakis, N., "Learning to Compare Image Patches via Convolutional Neural Networks,", CVPR, 2015

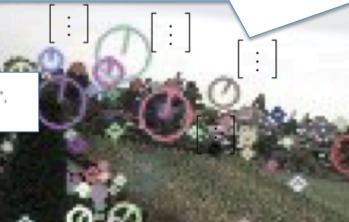
.



 Gauglitz, S., Turk, M., Höllerer, T., "Improving Keypoint Orientation Assignment,", BMVC, 2011



orientation estimation



descriptor computation

### Outline

- Introduction;
- Related work;
- some concepts related to your work
- your work
- Results and comparison;
- Conclusion and future work.



### No Outline!

- Introduction;
- Related work;
- some concepts related to your work
- your work
- Results and comparison;
- Conclusion and future work



### No Outline!

Possibly a list of the topics of your talk if it is in several parts;

Have transition slides between the different parts.





• 3D hand pose estimation and tracking.



Feature point detection and description.





 3D hand pose estimation and tracking.

Training a Feedback Loop for Hand Pose Estimation.

Markus Oberweger, Paul Wohlhart, and Vincent Lepetit.

ICCV'15. Oral



Feature point detection and description.





• 3D hand pose estimation and tracking.



Feature point detection and description.

LIFT: Learned Invariant Feature Transform.

Kwang Moo Yi, Eduard Trulls, Vincent

Lepetit, and Pascal Fua

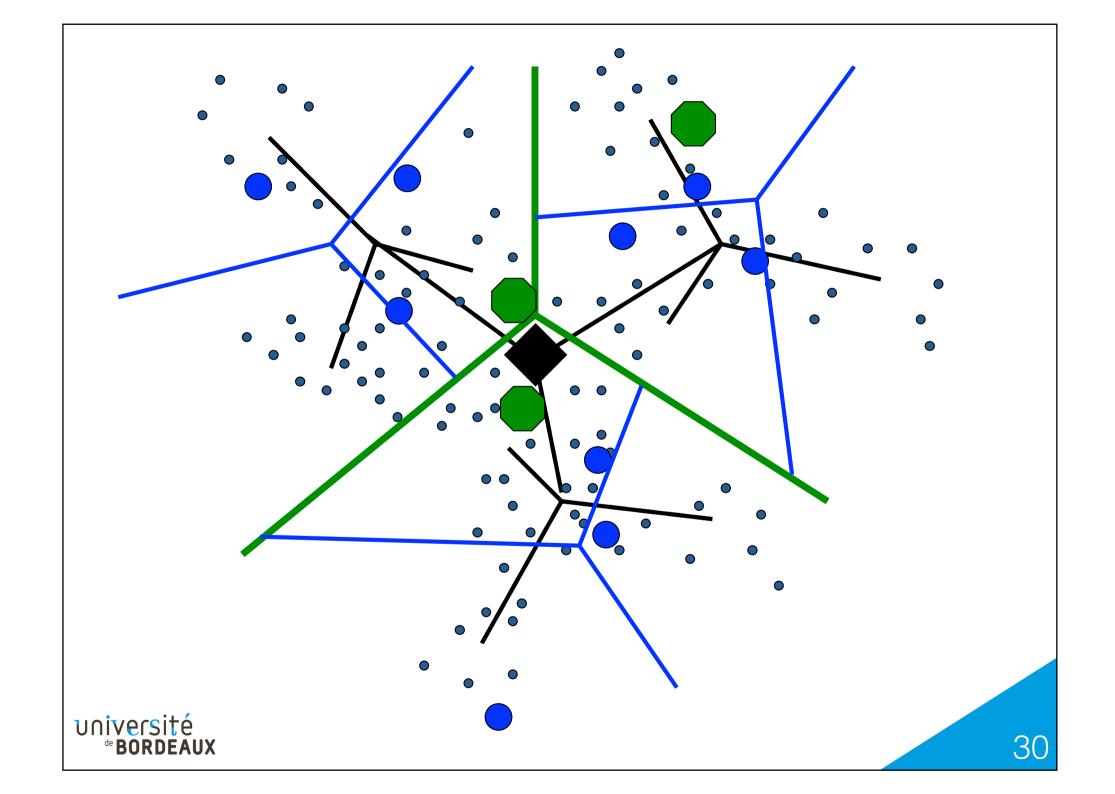
ECCV'16. Spotlight

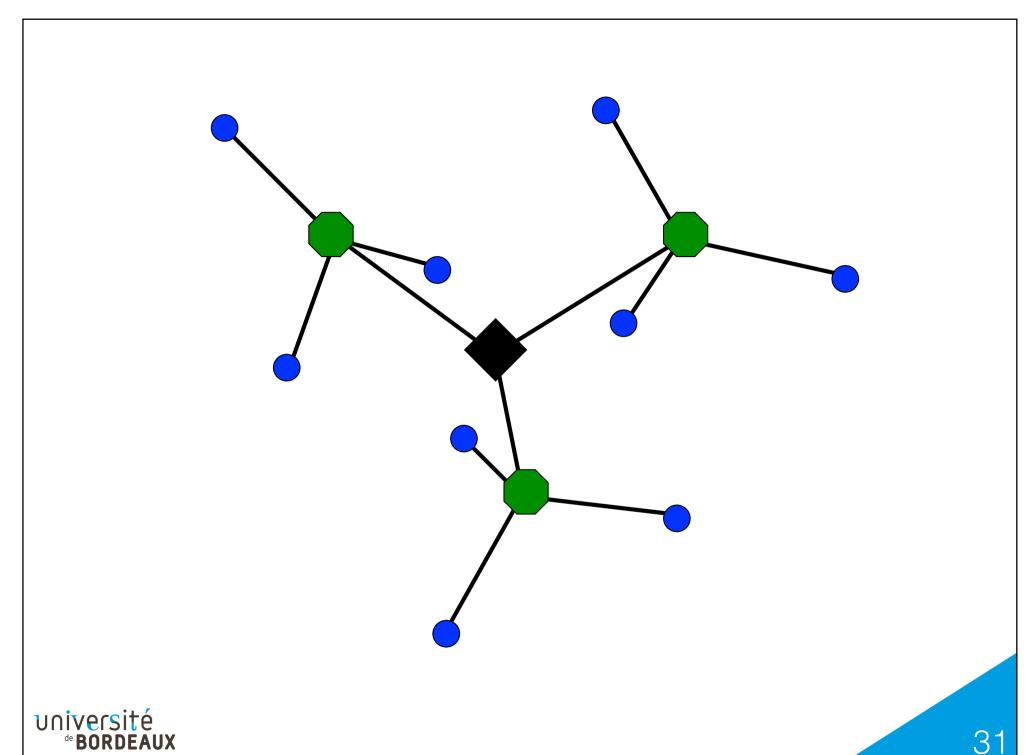


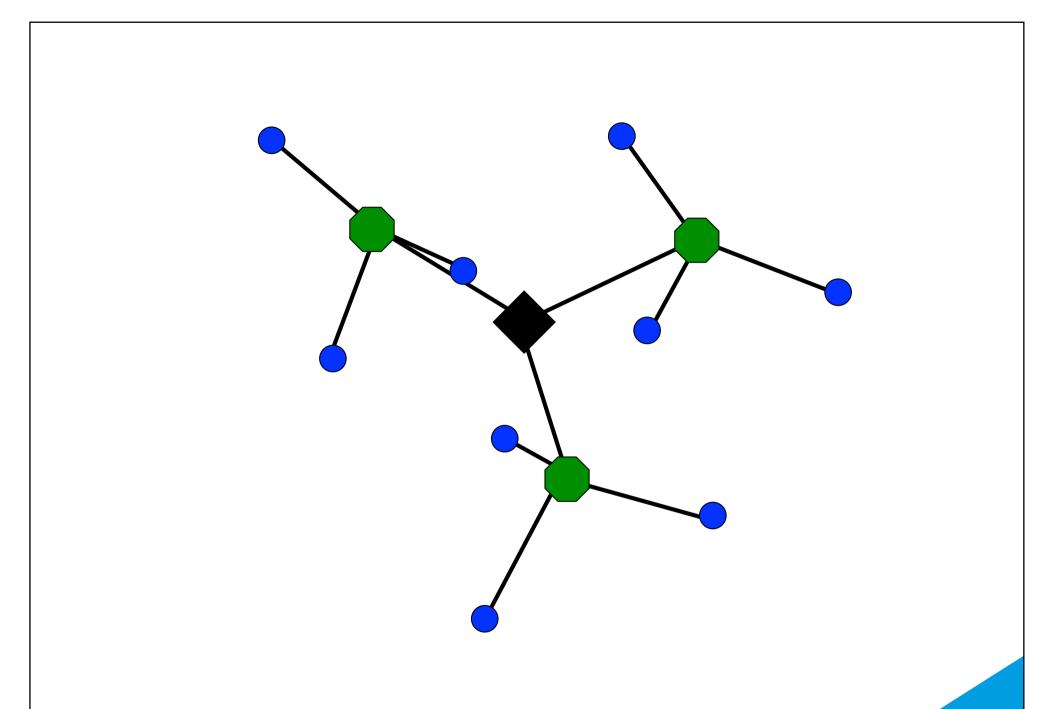
# Give the Intuition of your Contribution

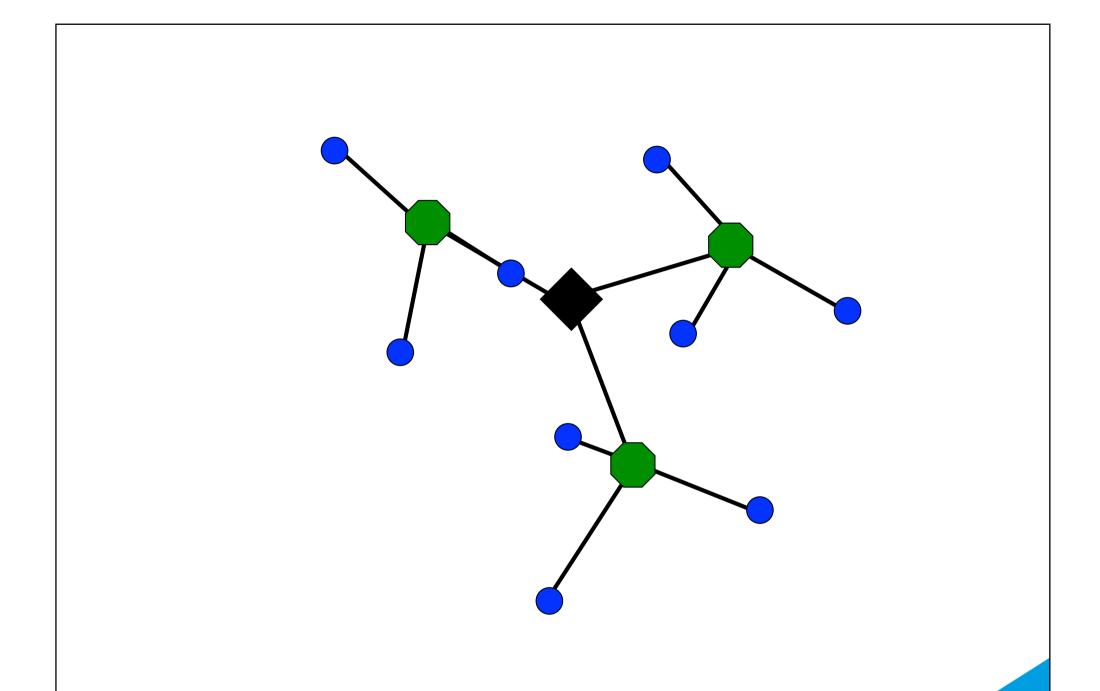




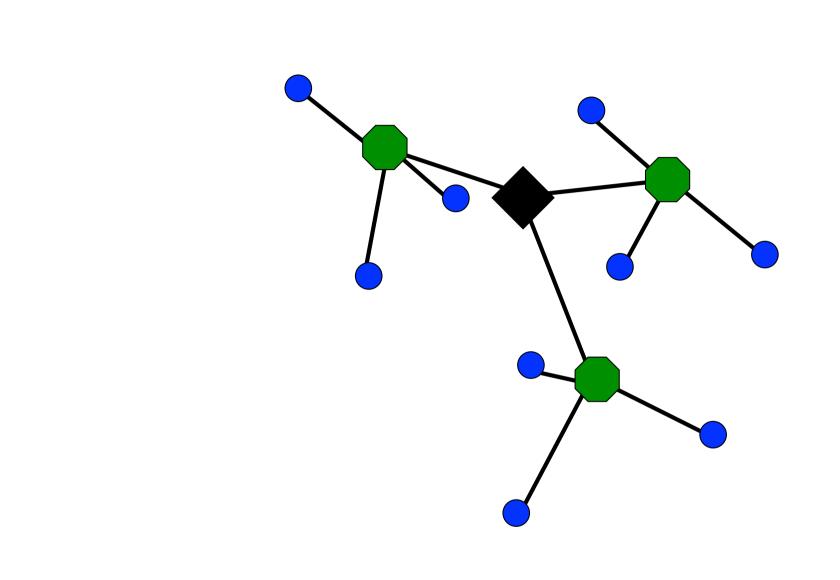




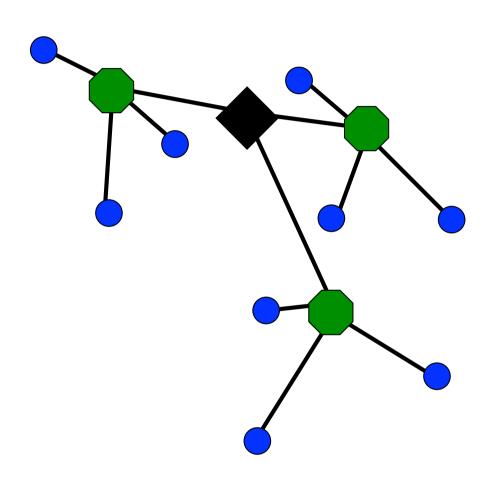




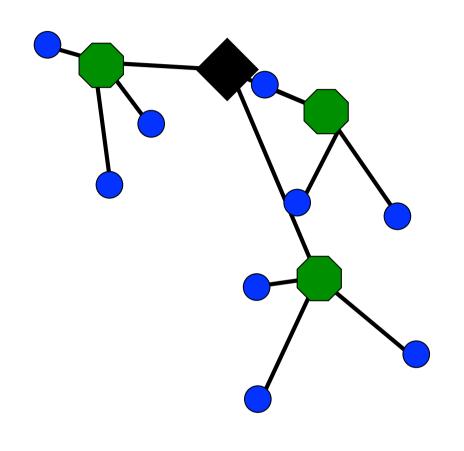
université BORDEAUX



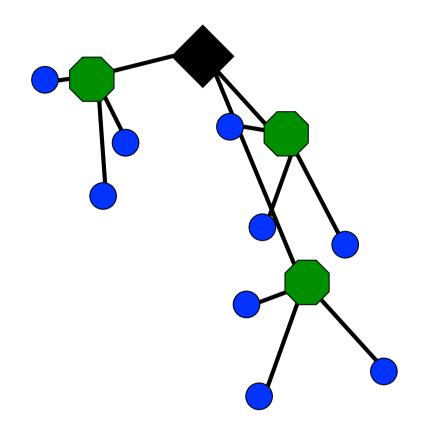
université BORDEAUX



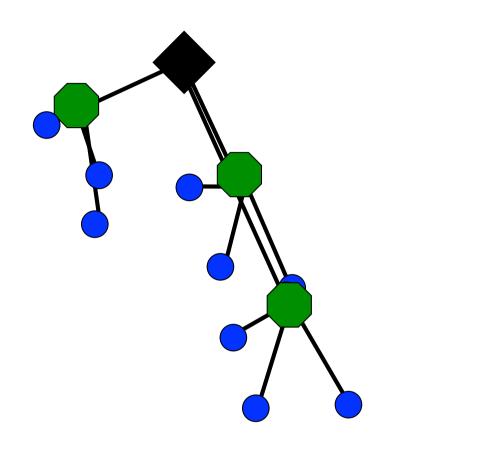




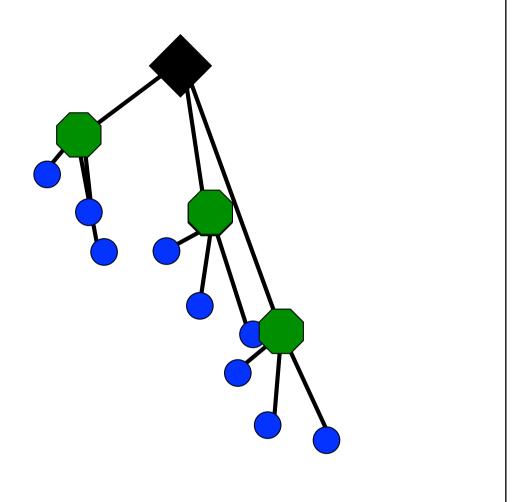




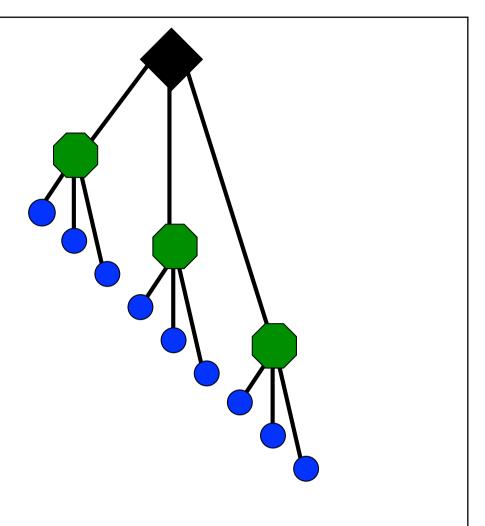




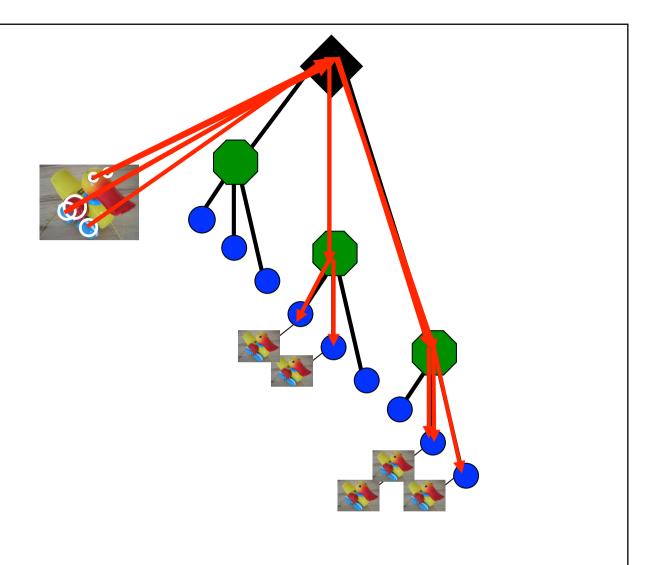




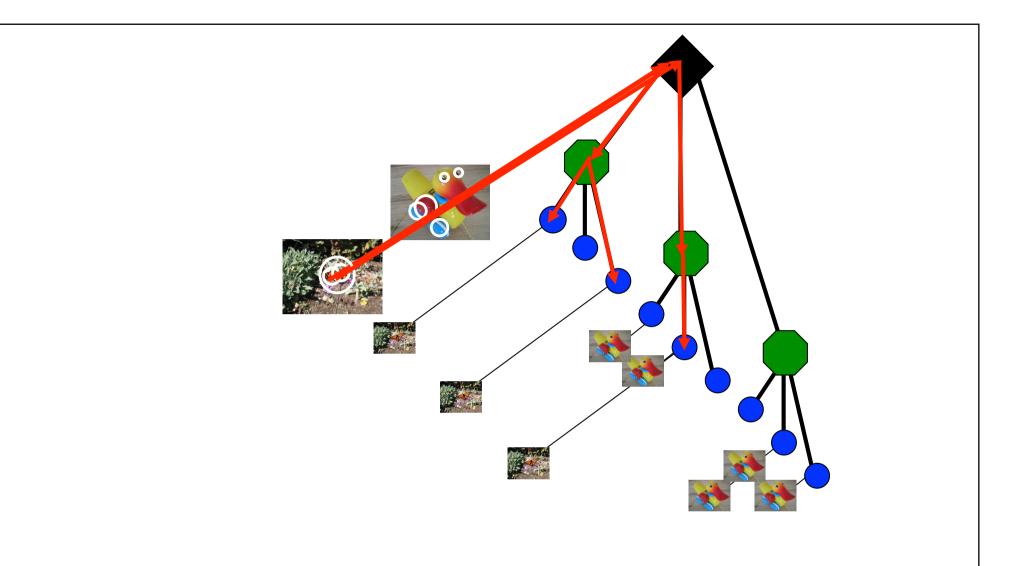




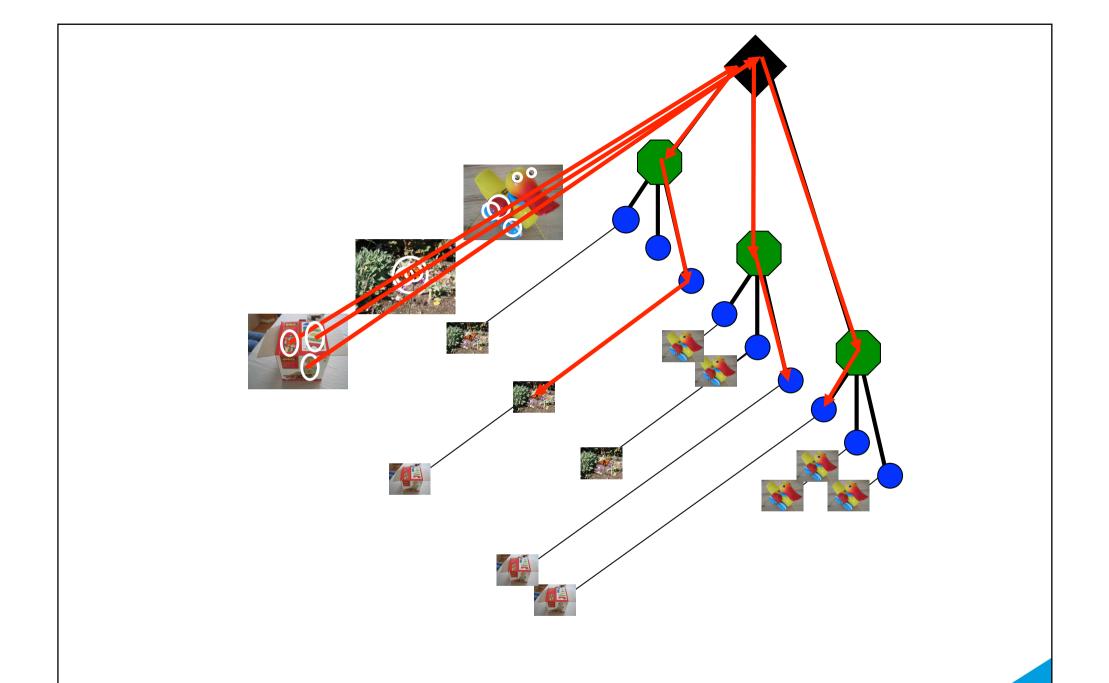




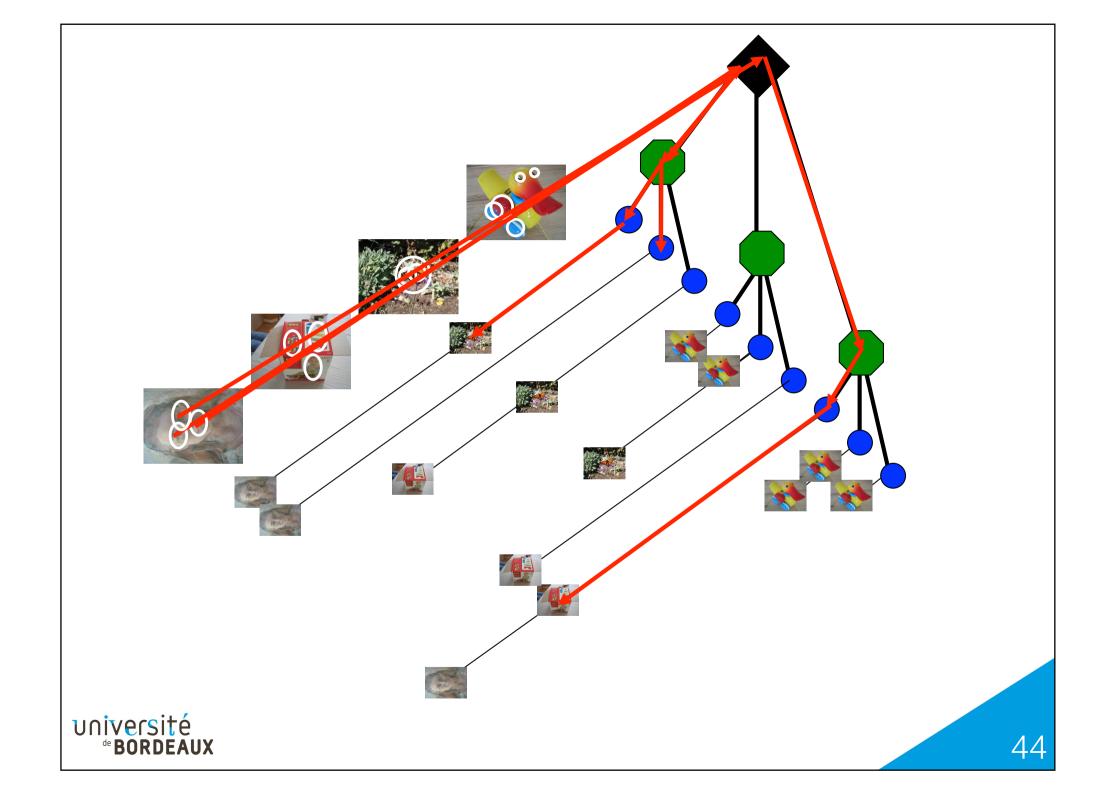


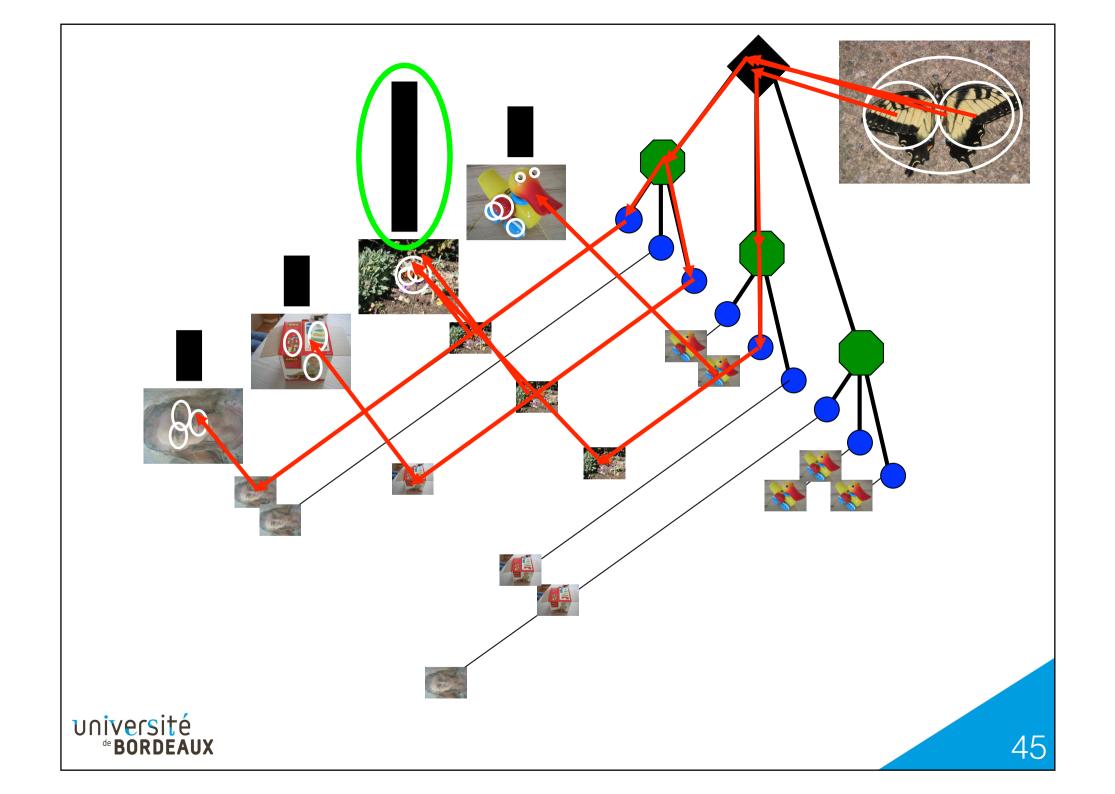






université BORDEAUX





# Timing

One idea / item per slide;

Rule of thumb: about 1 minute per slide.



### Formulas

# Be very careful!

$$egin{aligned} \mathcal{L}_{D_0} &= \mathbb{E}_{(I_0,t) \sim p_{data}}[\log D_0(I_0,arphi_t)] \ + \ \mathbb{E}_{z \sim p_z,t \sim p_{data}}[\log (1-D_0(G_0(z,\hat{c}_0),arphi_t))], \ \\ \mathcal{L}_{G_0} &= \mathbb{E}_{z \sim p_z,t \sim p_{data}}[\log (1-D_0(G_0(z,\hat{c}_0),arphi_t))] \ + \ \lambda D_{\mathit{KL}}(\mathcal{N}(\mu_0(arphi_t),\Sigma_0(arphi_t))) \| \mathcal{N}(0,I)). \end{aligned}$$



$$\mathbf{h} = g(\mathbf{W}\mathbf{x} + \mathbf{b})$$
$$\mathbf{y}(\mathbf{x}) = \mathbf{W}_2\mathbf{h} + \mathbf{b}_2$$

How can we find  $\mathbf{W}$ ,  $\mathbf{b}$ ,  $\mathbf{W}_2$ , and  $\mathbf{b}_2$ ?

[Rumelhart, Hinton, Williams] introduces an objective (or loss) function:

$$\mathcal{L}(\mathcal{T}) = \sum_{(\mathbf{x}, \mathbf{d}) \in \mathcal{T}} \|\mathbf{y}(\mathbf{x}) - \mathbf{d}\|^2$$



$$\mathbf{h} = g(\mathbf{W}\mathbf{x} + \mathbf{b})$$
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 $\mathcal{T}$ : training set



$$\mathbf{h} = g(\mathbf{W}\mathbf{x} + \mathbf{b})$$
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 $\mathcal{T}$ : training set

x: 1 training example;

d: the desired output for x.



$$\mathbf{h} = g(\mathbf{W}\mathbf{x} + \mathbf{b})$$
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[Rumelhart, Hinton, Williams] introduces an objective (or loss) function:

$$\mathcal{L}(\mathcal{T}) = \sum_{(\mathbf{x}, \mathbf{d}) \in \mathcal{T}} \| \underline{\mathbf{y}}(\mathbf{x}) - \mathbf{d} \|^2$$

 $\mathbf{y}(\mathbf{x})$ : network output for  $\mathbf{x}$ 

 $\mathcal{T}$ : training set

x: 1 training example;

d: the desired output for x.



### Formulas

If you use the same terms over several slides, make sure the audience did not forget them.



### **Descriptor Learning**

**Training**: from a training set  $\{((\mathbf{x}_n, \mathbf{y}_n), l_n)\}$ , find  $k_d(.)$  functions and weights  $\alpha_d$  that minimize:

one sample:

a pair of image patches

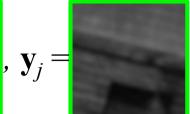
$$\sum_{n=1}^{N} \exp\left(-l_n \sum_{d=1}^{L} \alpha_d c_d(\mathbf{x}_n, \mathbf{y}_n)\right)$$

label for the sample (+1 or -1)

$$c_d(\mathbf{x}_n, \mathbf{y}_n) = k_d(\mathbf{x}_n) k_d(\mathbf{y}_n)$$

$$\mathbf{x}_i = \begin{bmatrix} \mathbf{y}_i \\ \mathbf{y}_i \end{bmatrix}, \ \mathbf{y}_i = \begin{bmatrix} \mathbf{y}_i \\ \mathbf{y}_i \end{bmatrix}$$

$$\mathbf{x}_{j} = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$



$$l_{j} = -1$$

### **Descriptor Learning**

**Training**: find  $k_d(.)$  functions and weights  $\alpha_d$  that minimize:

$$\sum_{n=1}^{N} \exp\left(-l_n \sum_{d=1}^{L} \alpha_d c_d(\mathbf{x}_n, \mathbf{y}_n)\right)$$

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$$c_d(\mathbf{x}_n, \mathbf{y}_n) = k_d(\mathbf{x}_n) k_d(\mathbf{y}_n)$$

At run-time: given two *new* image patches x and y, first compute

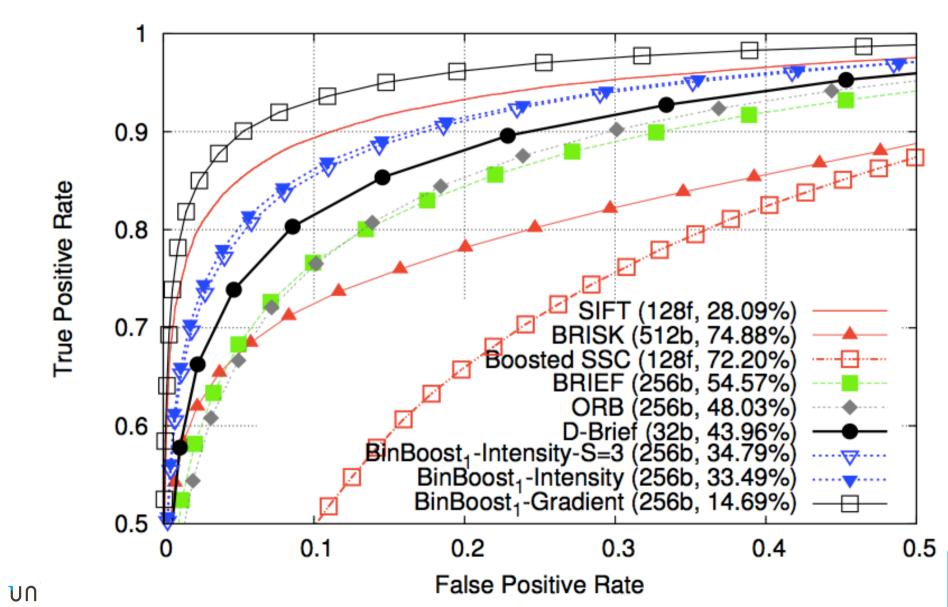
descriptor(
$$\mathbf{x}$$
) =  $[\sqrt{\alpha_1}k_1(\mathbf{x}), \dots \sqrt{\alpha_L}k_L(\mathbf{x})]^{\top}$   
descriptor( $\mathbf{y}$ ) =  $[\sqrt{\alpha_1}k_1(\mathbf{y}), \dots \sqrt{\alpha_L}k_L(\mathbf{y})]^{\top}$ 

You can use plain names for variables.

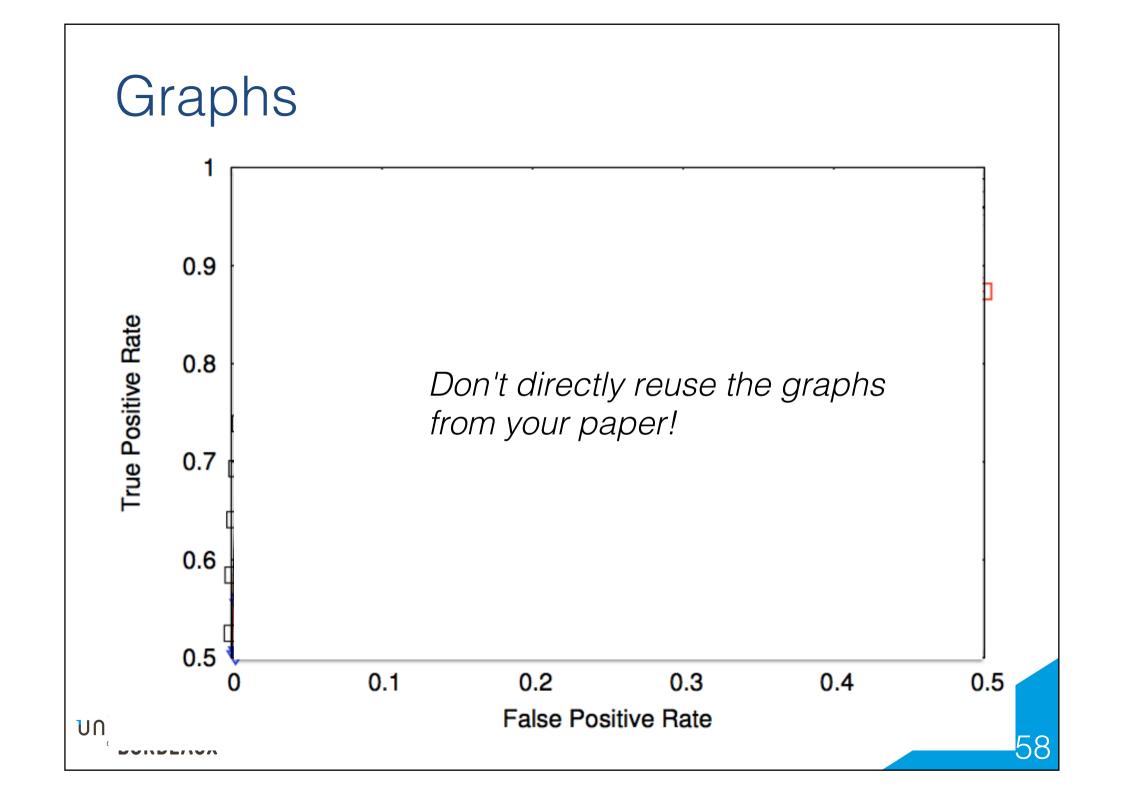
# Graphs

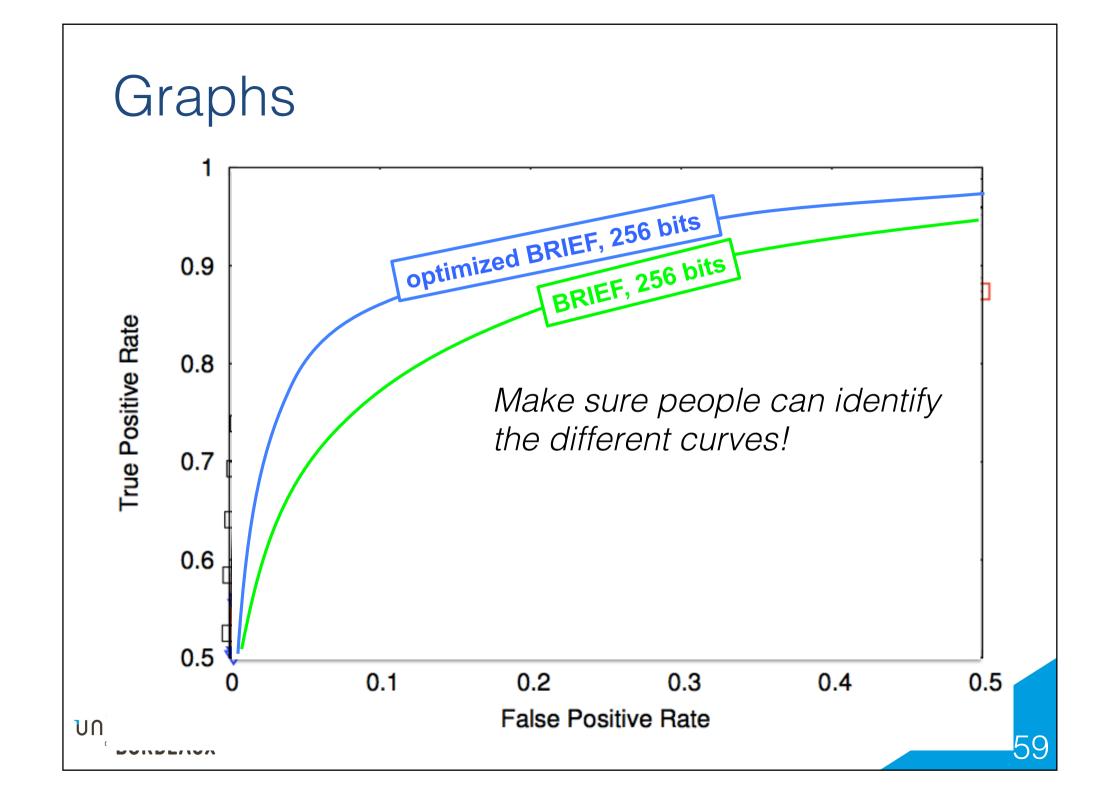


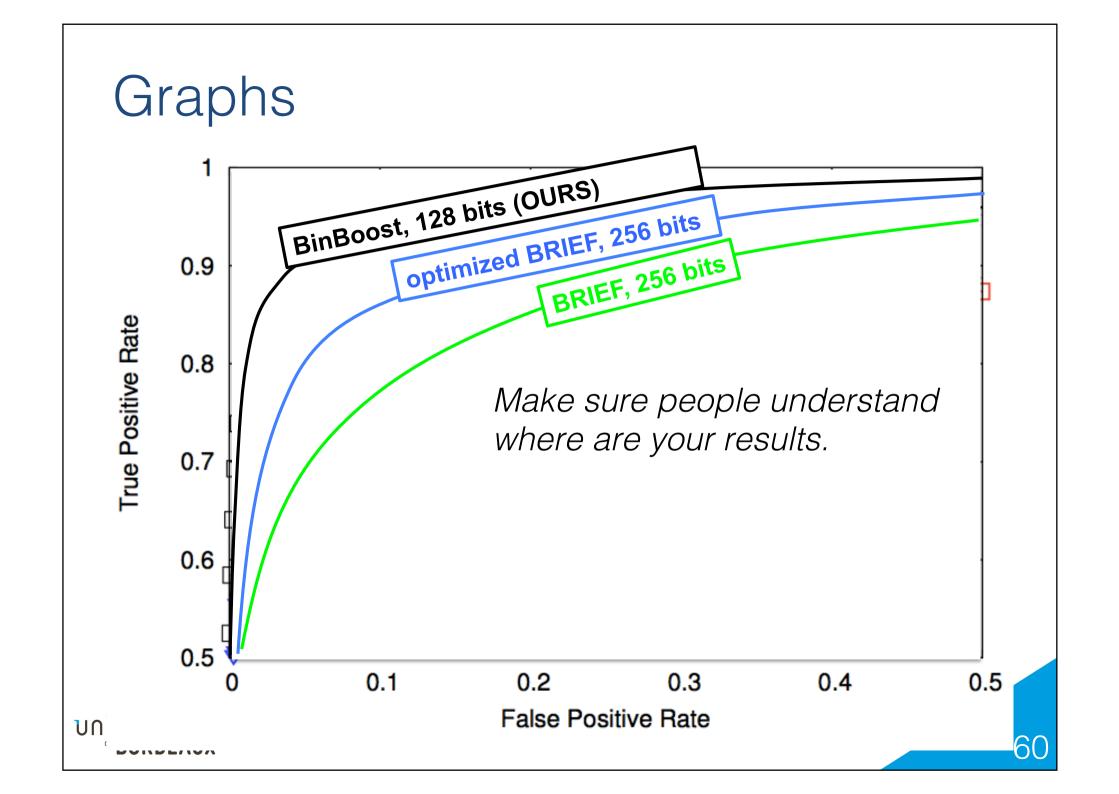
# Graphs



57







# Use PowerPoint/Keynote (except if you really have a lot of maths):

50 Thousand Images

- you can draw figures easily;
- you can do last minute changes easily;

- you can see your script during the

presentation;

But be careful!



### Title

- First item;
- Second item;
  - First sub-item;

- This is boring;
- And difficult to remember.

The format Powerpoint/ Keynote encourages makes the slides difficult to remember (and boring).



### Animations

Don't use fancy effects

But constructing the slide progressively can be interesting sometimes.

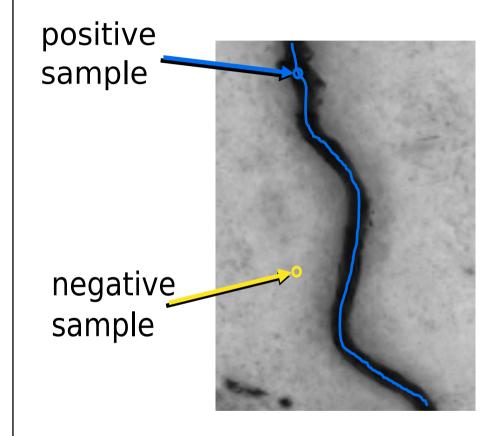


### Centerline Detection as a Classification Problem



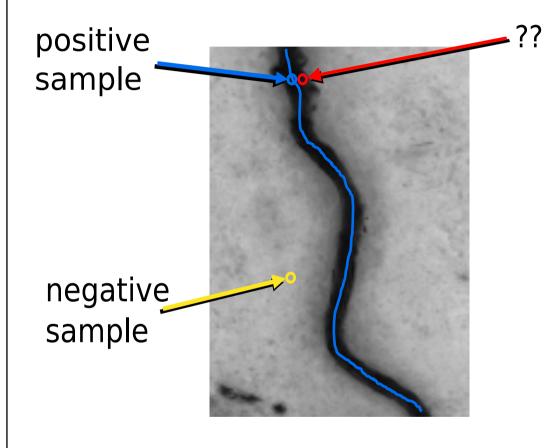
Input image

### Centerline Detection as a Classification Problem



Input image

### Centerline Detection as a Classification Problem



# Presenting your Talk



Rehearse (in front of people!)

Be enthusiastic!



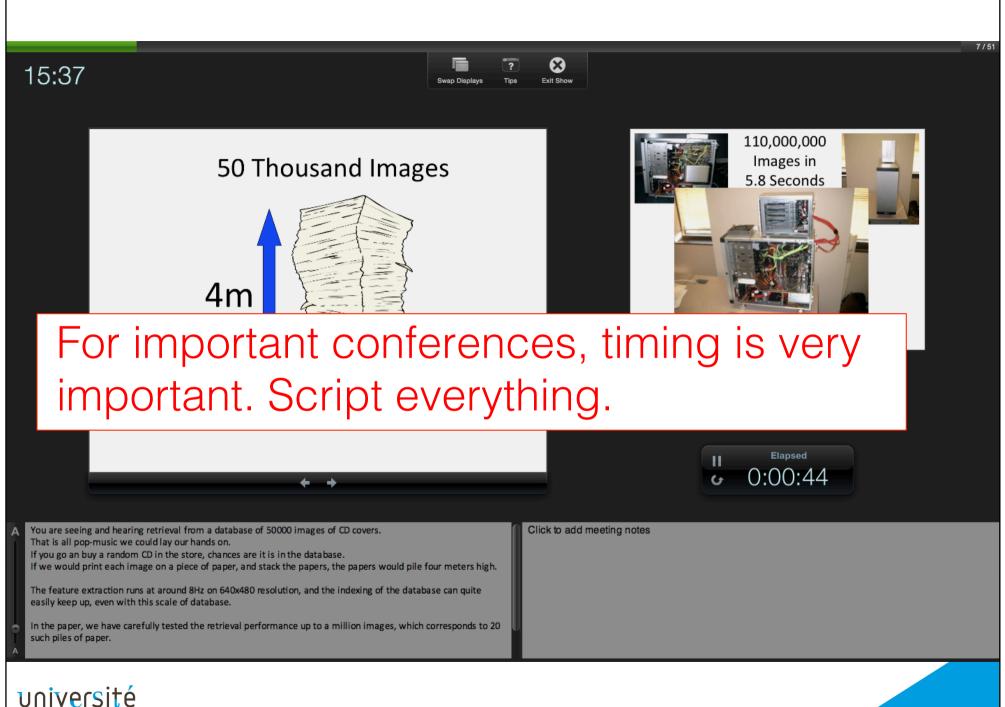
# Everybody is Nervous

Deep breathing before;



• Script your first sentences precisely.







### Watch Online Videos

Observe what the presenter did when you understand/are interested/are lost/are bored.

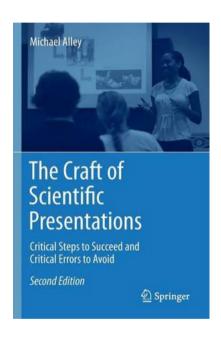








### A Good Reference



The Craft of Scientific Presentations (second edition) Michael Alley

Springer



# Make Sure the Audience Understands when You Are Done

Thanks!

Questions?

