



Deep Learning: Searching for Images

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Visual product recommender

I want to buy new shoes, but...



Too many
options online...



Text search doesn't help...



"Dress shoes"



Visual product search demo



Features are key to
machine learning

Goal: revisit classifiers, but using more complex, non-linear features

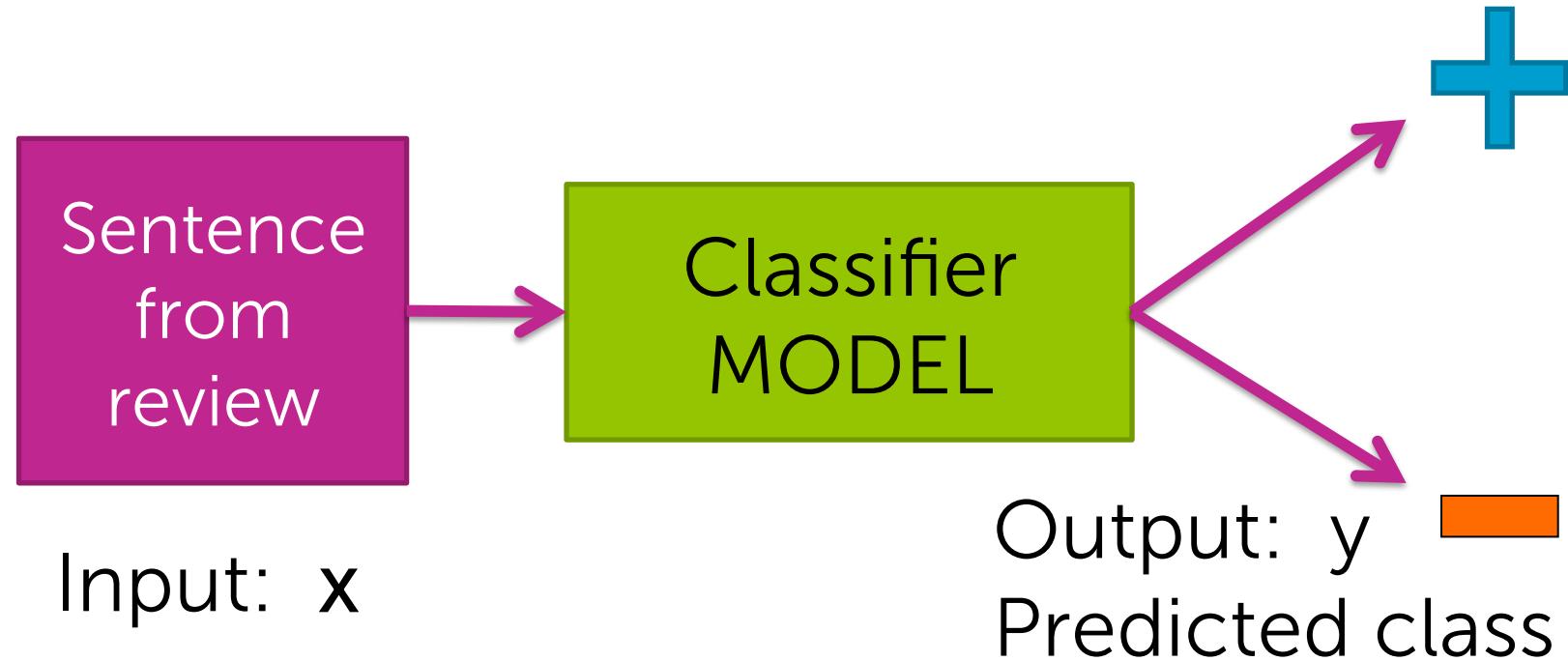
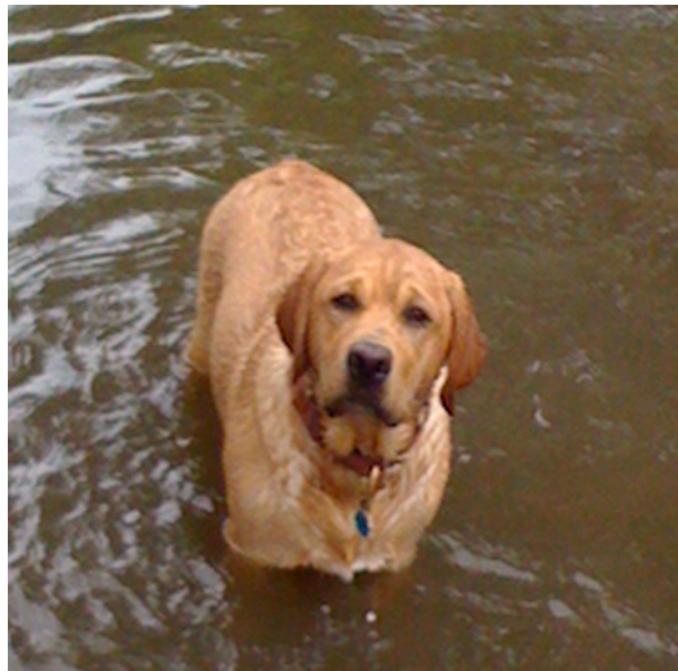


Image classification



Input: x
Image pixels

Output: y
Predicted object

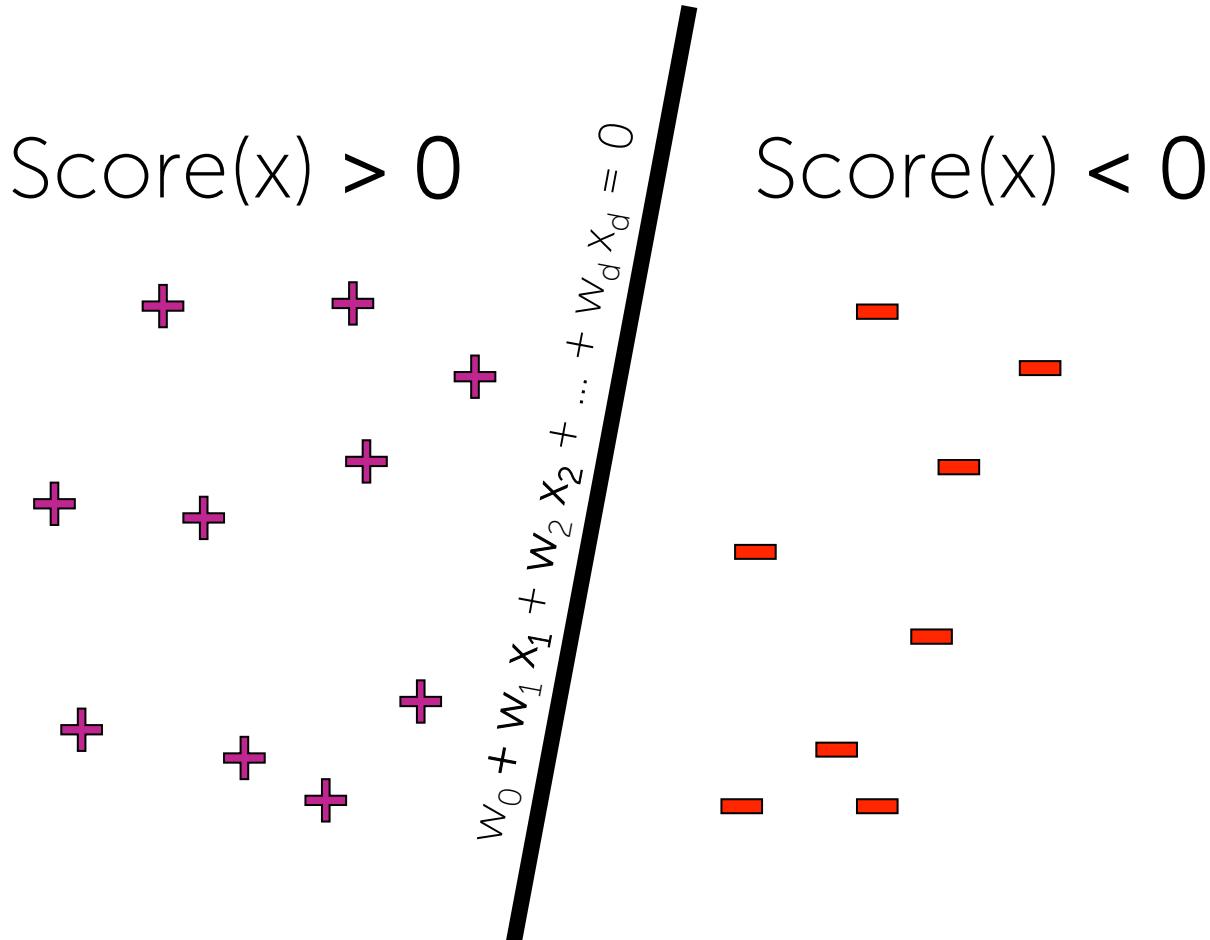
Neural networks



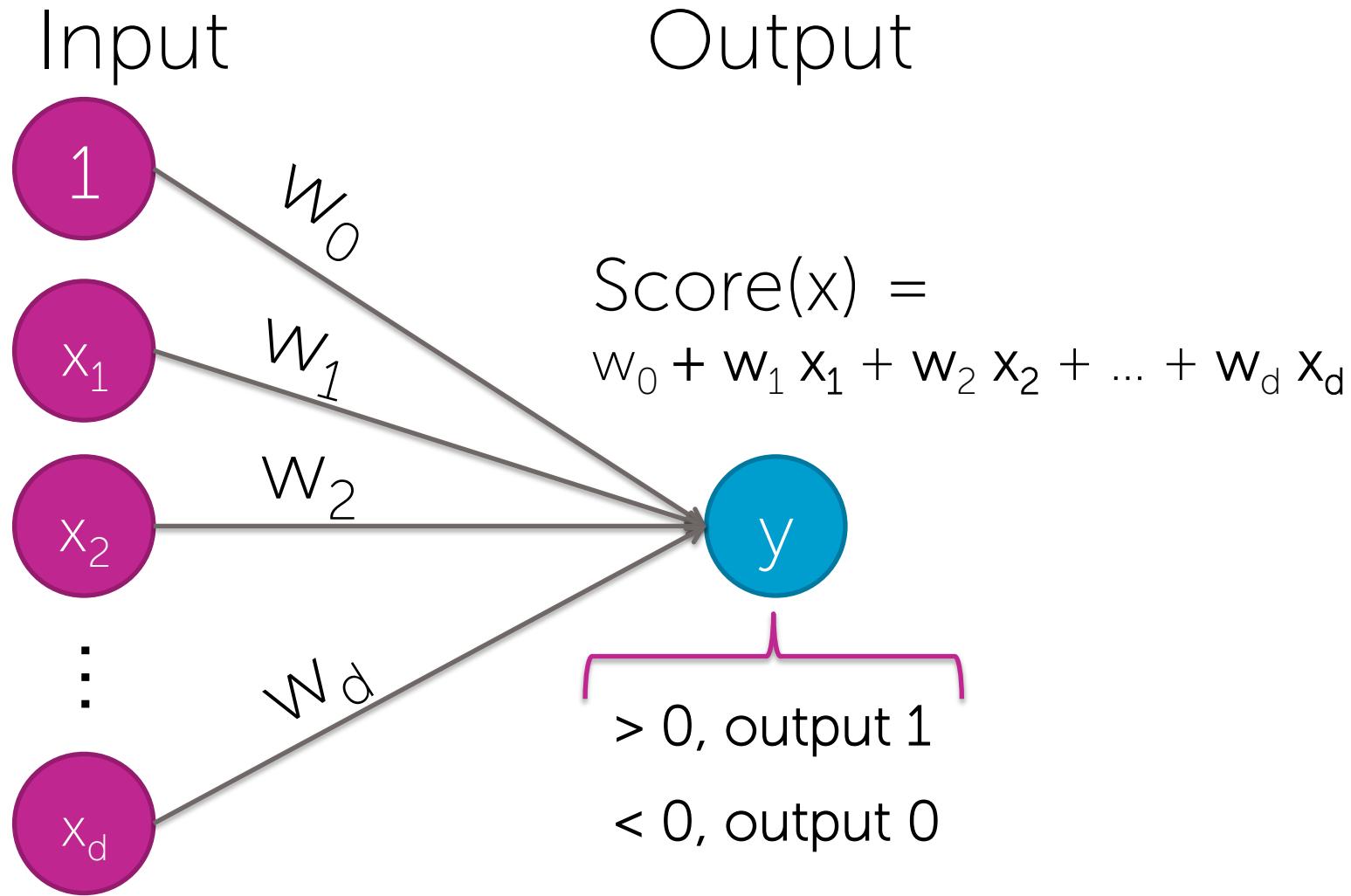
Learning ***very***
non-linear features

Linear classifiers

$$\text{Score}(x) = w_0 + w_1 x_1 + w_2 x_2 + \dots + w_d x_d$$

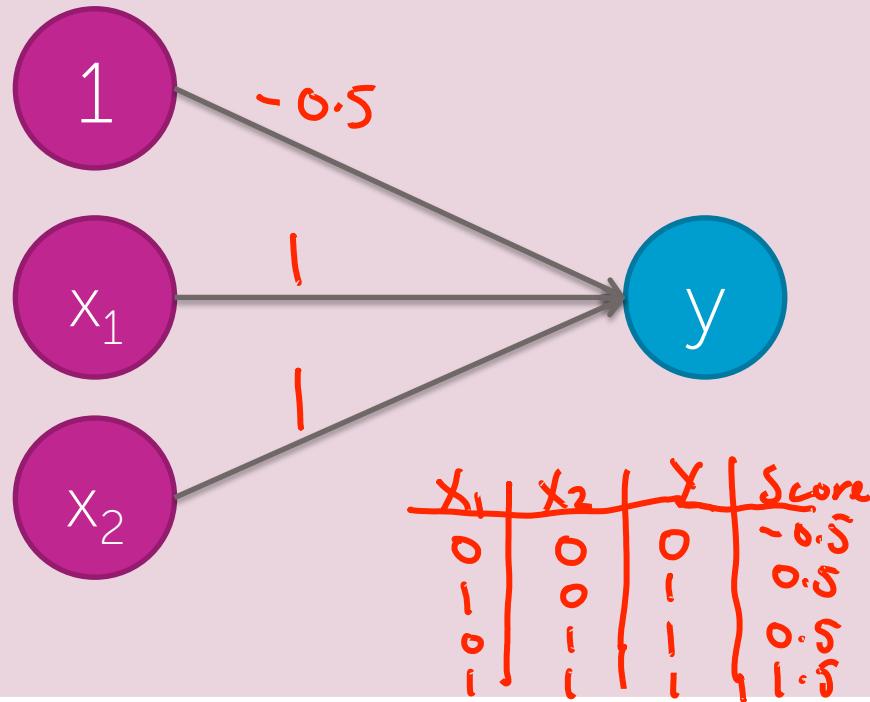


Graph representation of classifier: useful for defining neural networks

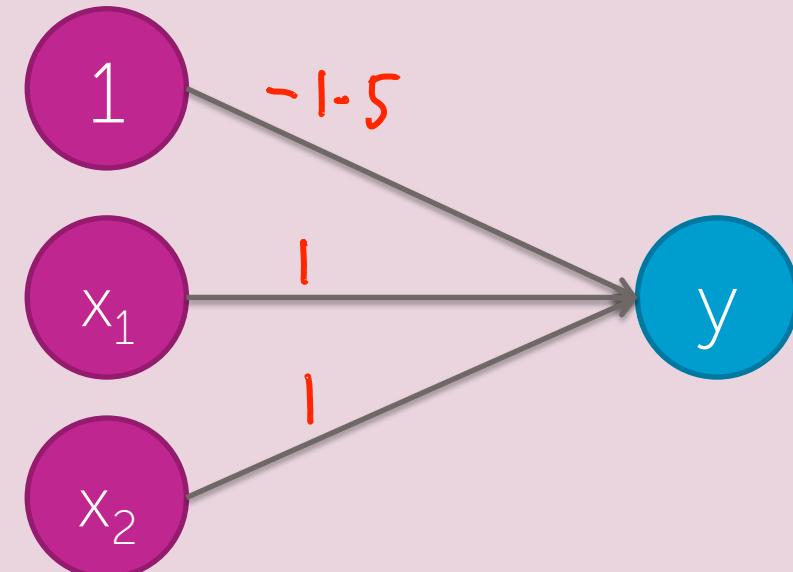


What can a linear classifier represent?

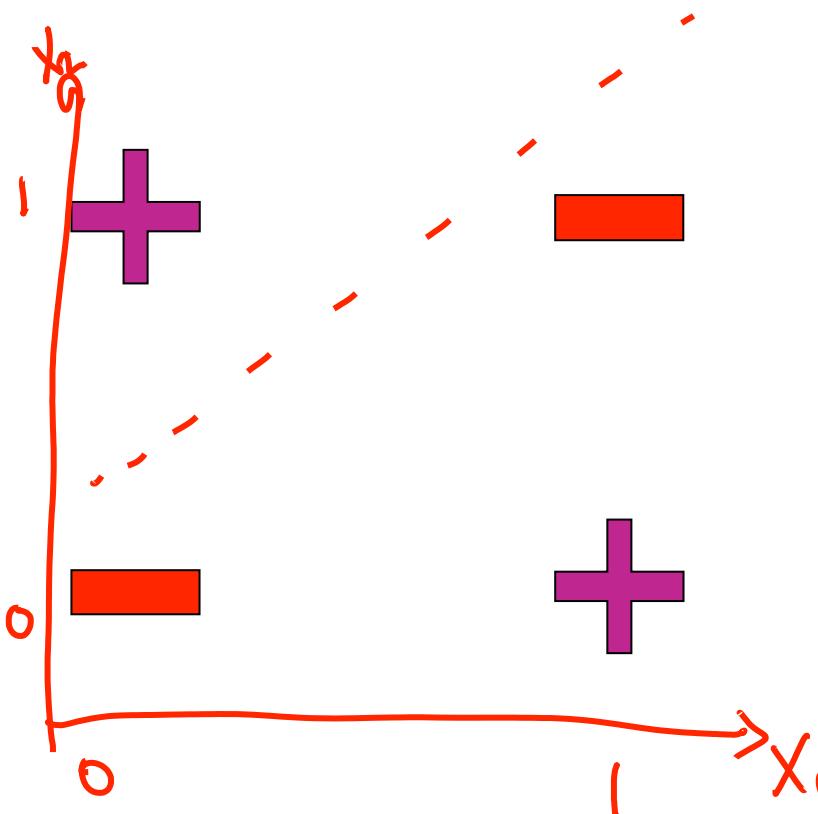
$x_1 \text{ OR } x_2$



$x_1 \text{ AND } x_2$



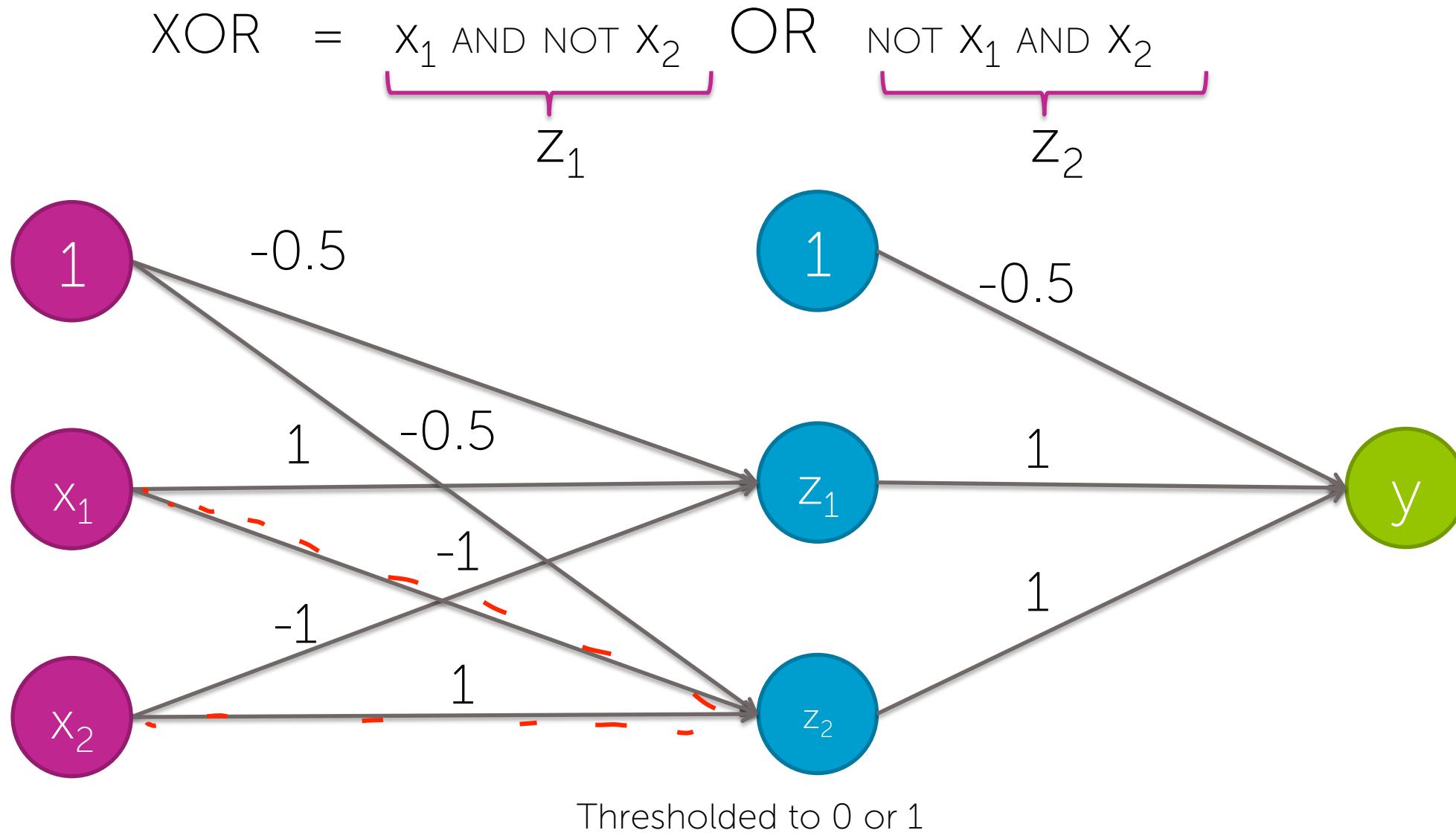
What can't a simple linear classifier represent?



XOR
the counterexample
to everything

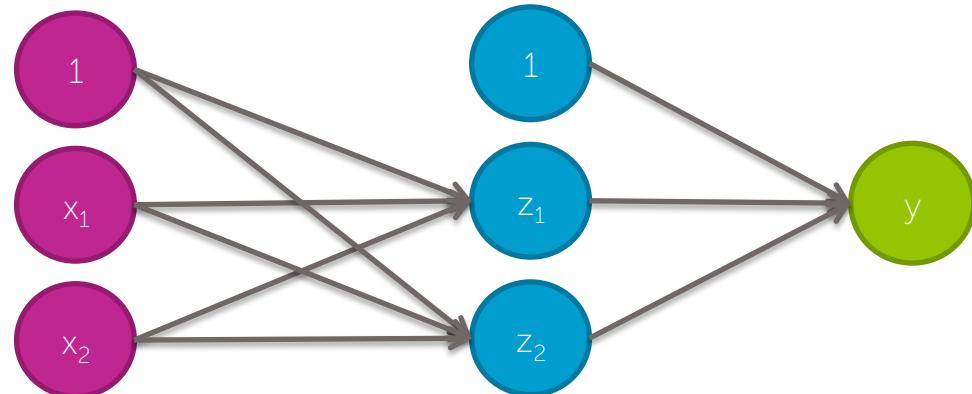
Need non-linear features

Solving the XOR problem: Adding a layer



A neural network

- Layers and layers and layers of linear models and non-linear transformations

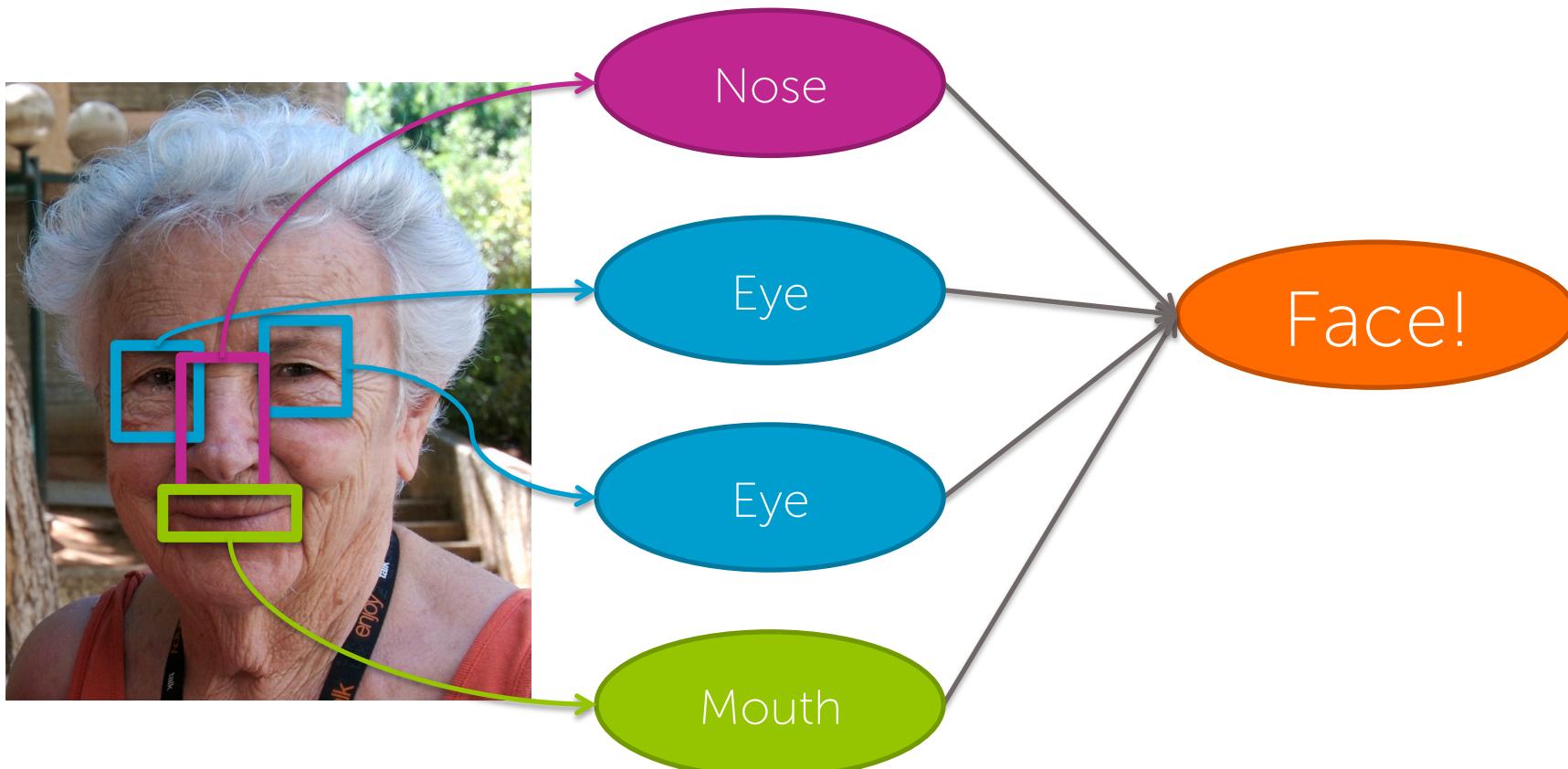


- Around for about 50 years
 - Fell in “disfavor” in 90s
- In last few years, big resurgence
 - Impressive accuracy on several benchmark problems
 - Powered by huge datasets, GPUs, & modeling/learning alg improvements

Application of deep learning to computer vision

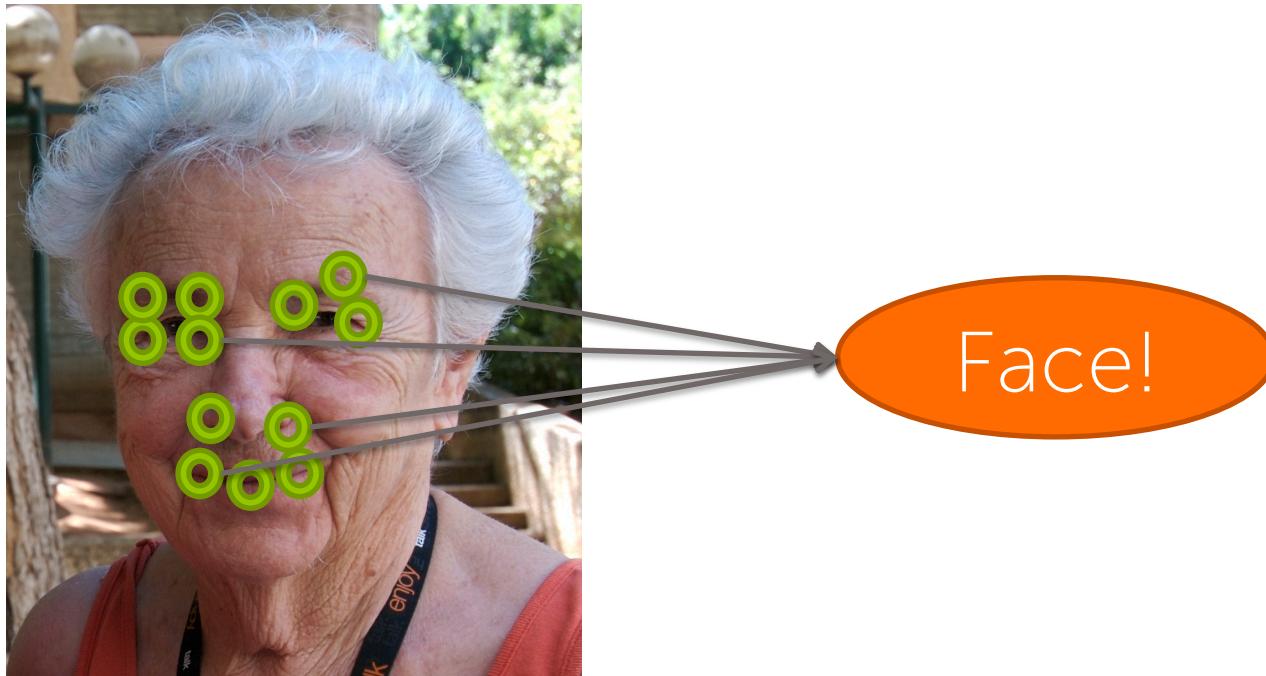
Image features

- Features = local detectors
 - Combined to make prediction
 - (in reality, features are more low-level)

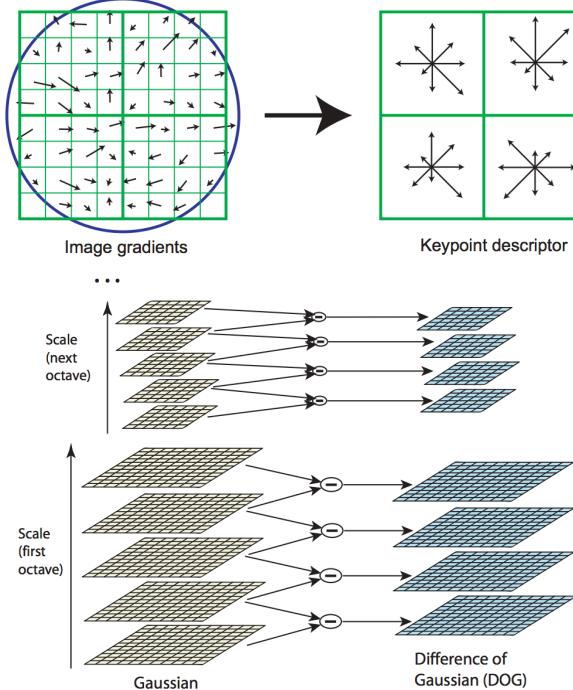


Typical local detectors look for locally “interesting points” in image

- *Image features*: collections of locally interesting points
 - Combined to build classifiers



Many hand created features exist for finding interest points...



SIFT [Lowe '99]

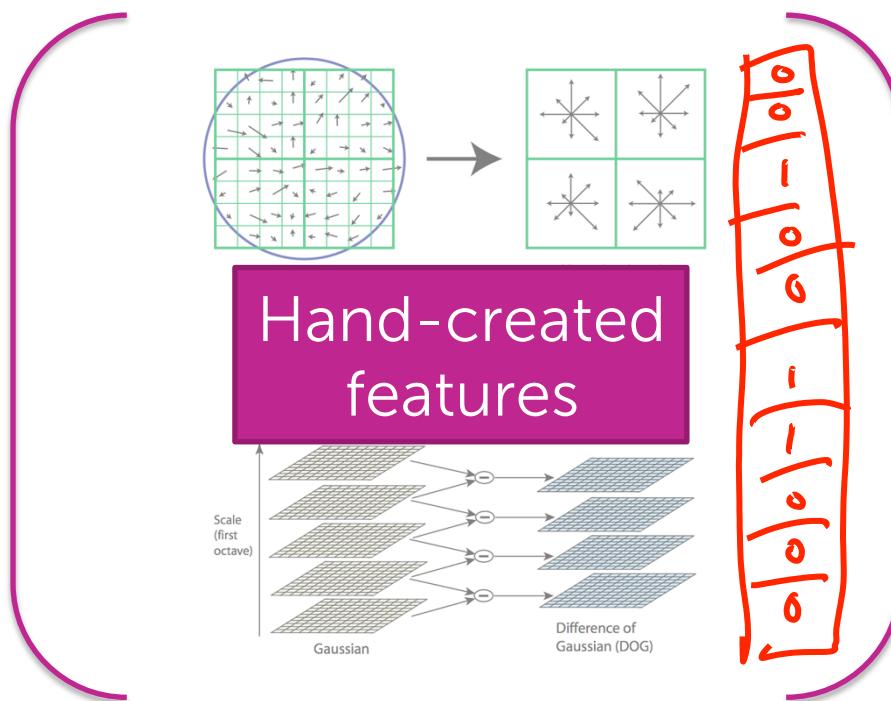
- *Spin Images*
[Johnson & Herbert '99]
- *Textons*
[Malik et al. '99]
- *RIFT*
[Lazebnik '04]
- *GLOH*
[Mikolajczyk & Schmid '05]
- *HoG*
[Dalal & Triggs '05]
- ...

Standard image classification approach

Input



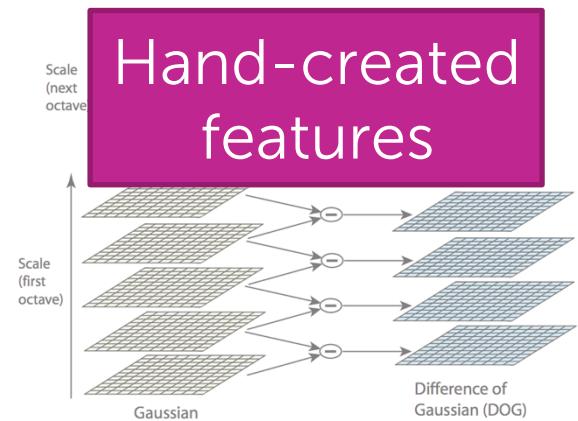
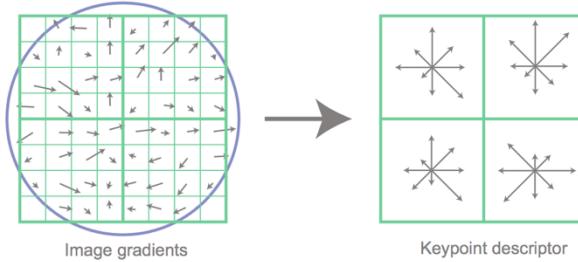
Extract features



Use simple classifier
e.g., logistic regression, SVMs

Face?

Many hand created features exist for finding interest points...



- *Spin Images*
[Johnson & Herbert '99]
- *Textons*
[Malik et al. '99]
- *RIFT*
[Lazebnik '04]
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[Mikolajczyk & Schmid '05]
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- ...

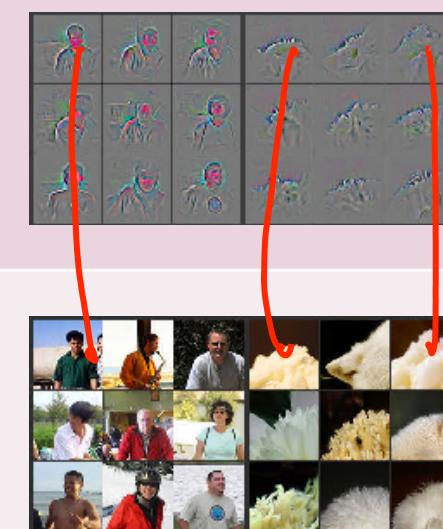
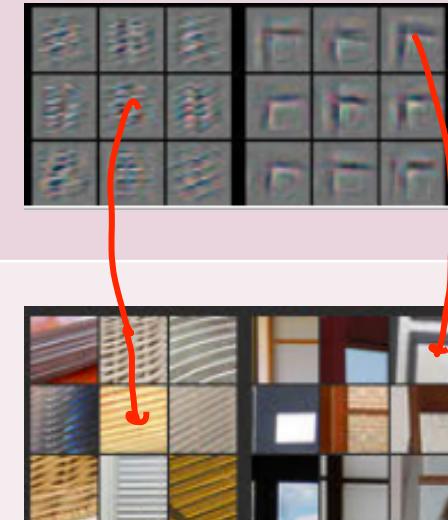
... but very painful to design

Deep learning: *implicitly learns features*



Example
detectors
learned

Example
interest
points
detected



[Zeiler & Fergus '13]

Deep learning performance

Sample results using deep neural networks

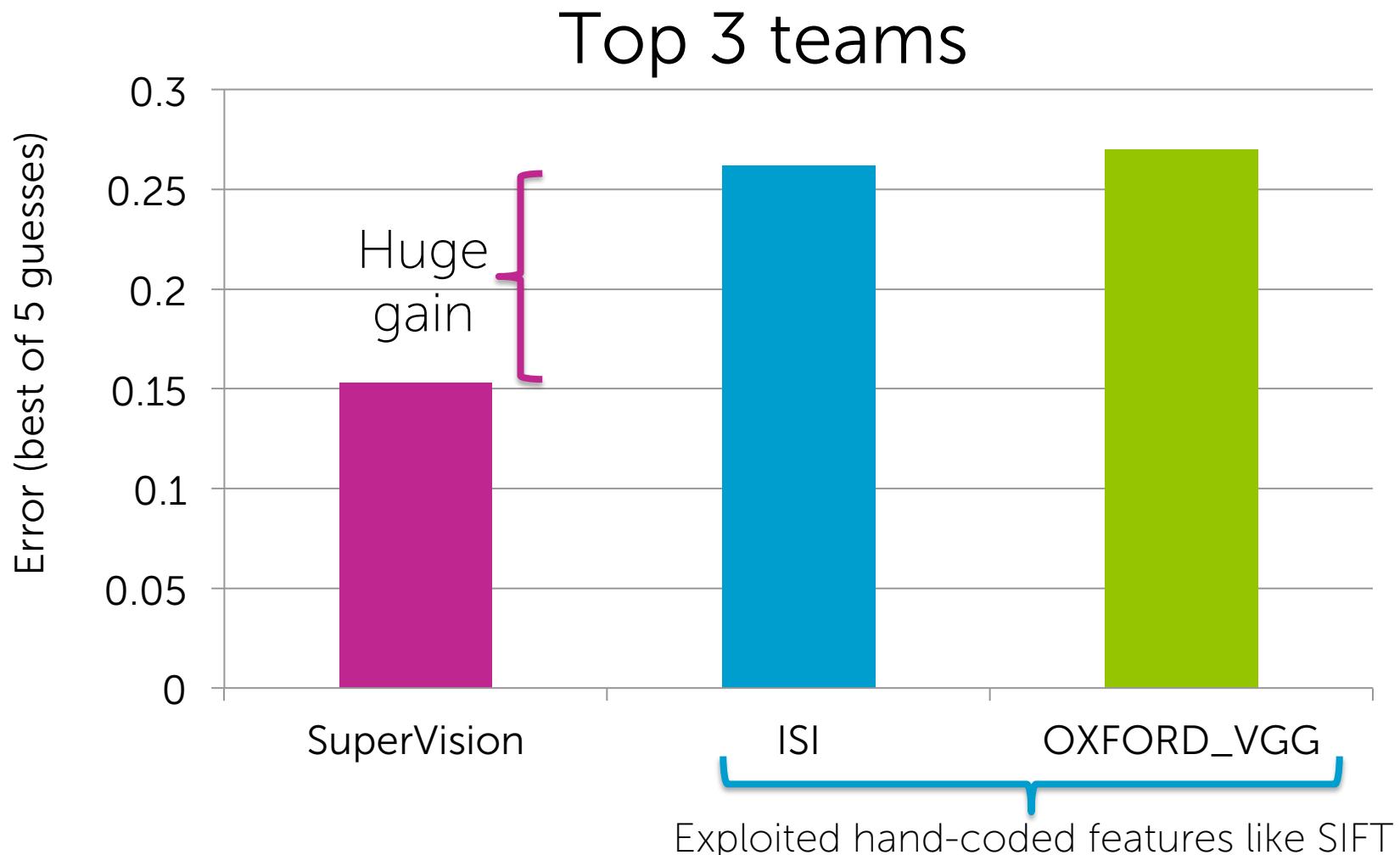
- German traffic sign recognition benchmark
 - 99.5% accuracy (IDSIA team)



- House number recognition
 - 97.8% accuracy per character [Goodfellow et al. '13]

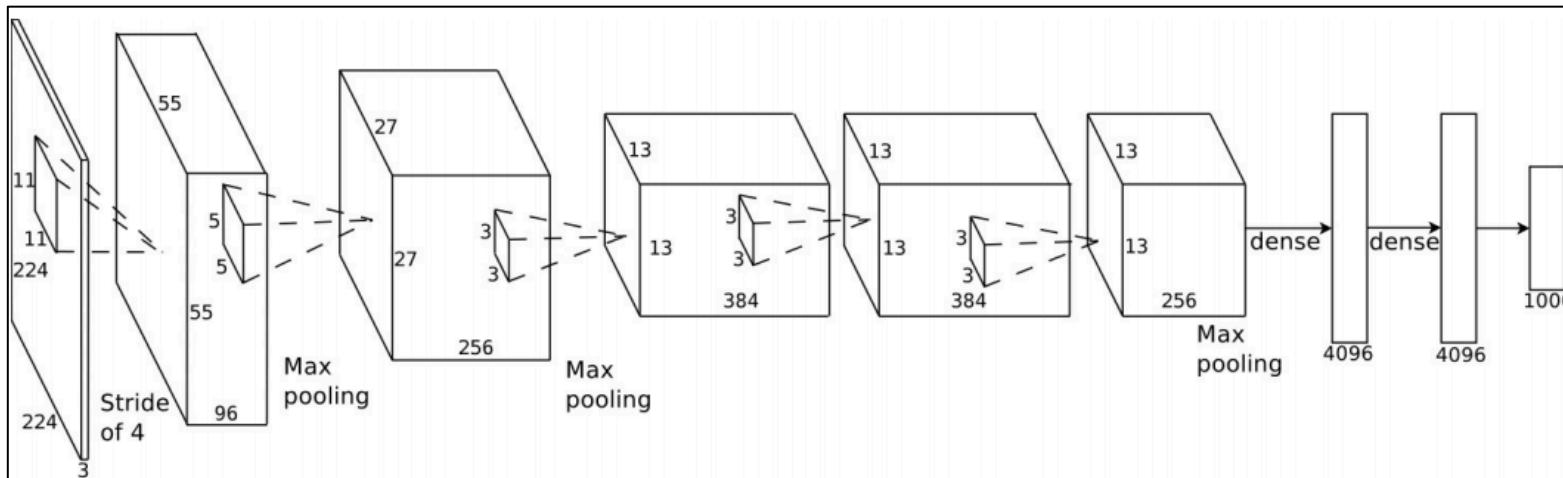


ImageNet 2012 competition: 1.2M training images, 1000 categories



ImageNet 2012 competition: 1.2M training images, 1000 categories

Winning entry: SuperVision
8 layers, 60M parameters [Krizhevsky et al. '12]

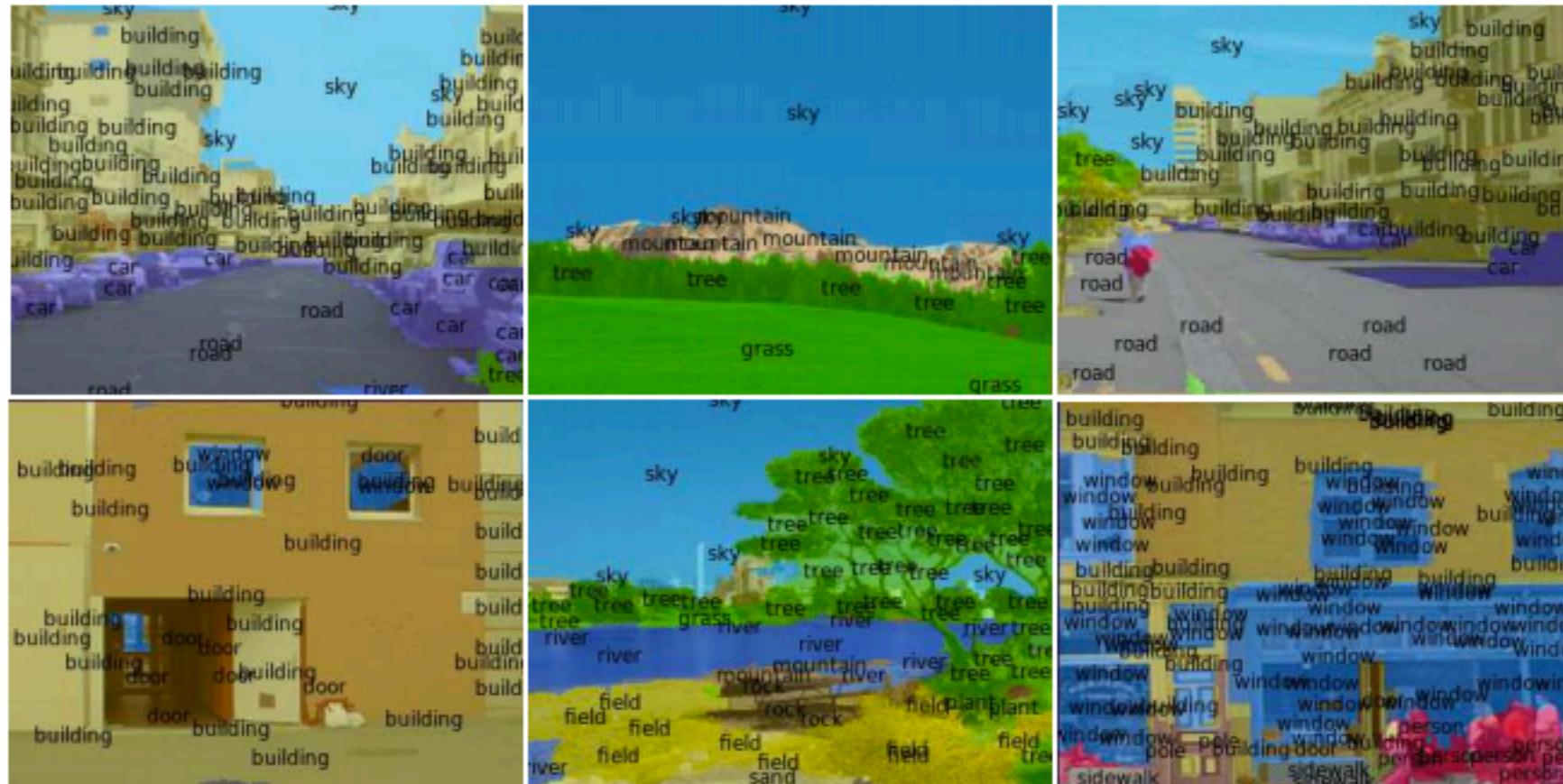


Achieving these amazing results required:

- New learning algorithms
- GPU implementation

Deep learning in computer vision

Scene parsing with deep learning



[Farabet et al. '13]

Retrieving similar images

Input Image



Nearest neighbors



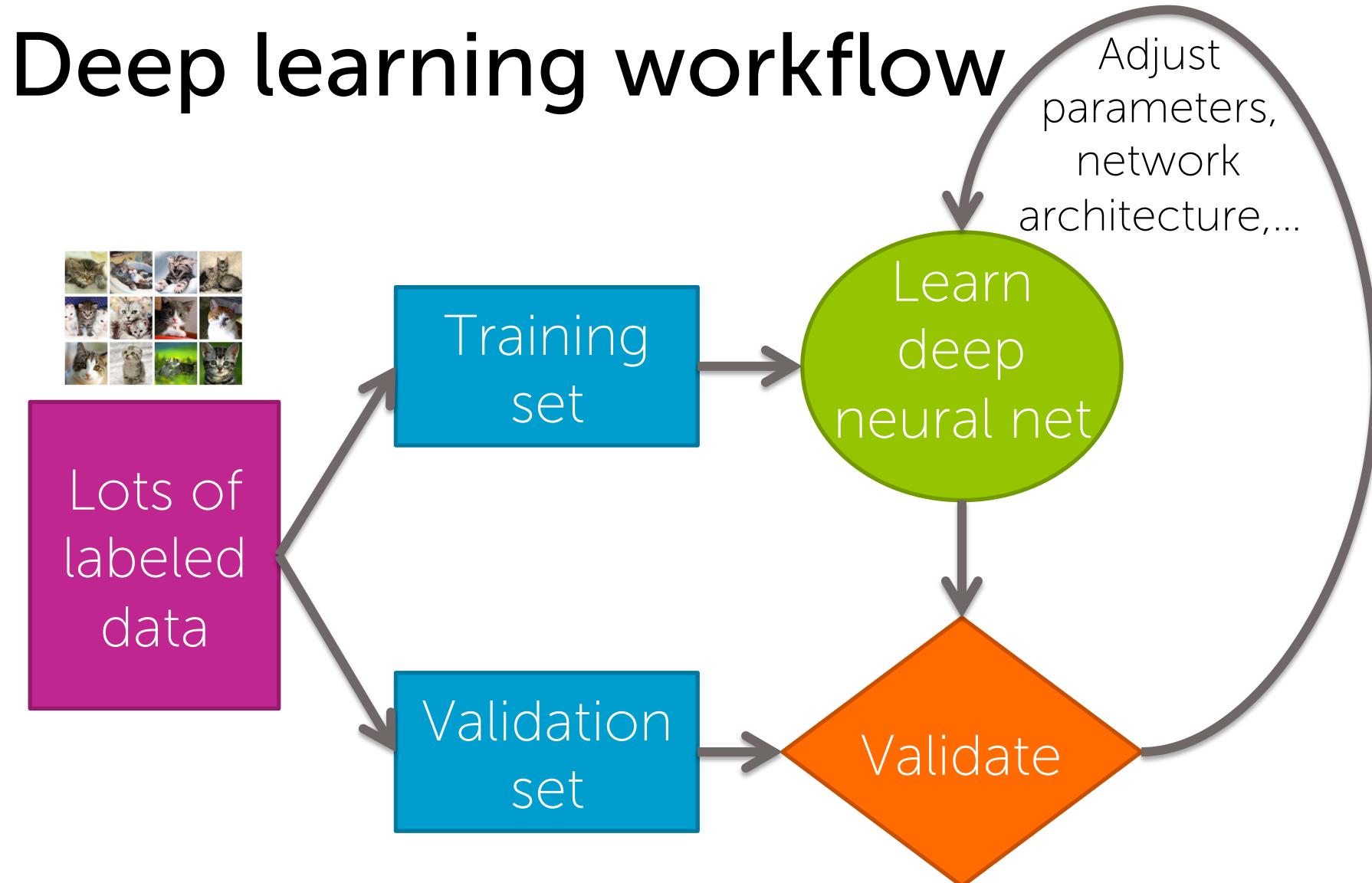
Challenges of deep learning

Deep learning score card

Pros

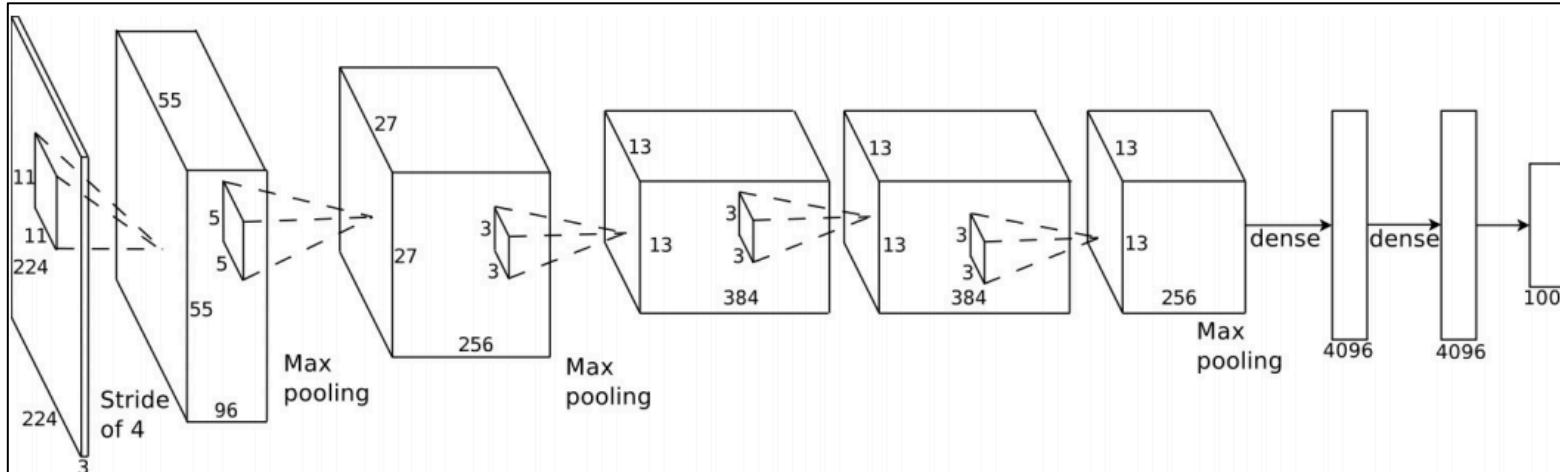
- Enables learning of features rather than hand tuning
- Impressive performance gains
 - Computer vision
 - Speech recognition
 - Some text analysis
- Potential for more impact

Deep learning workflow



Many tricks needed to work well...

Different types of layers, connections,...
needed for high accuracy



[Krizhevsky et al. '12]

Deep learning score card

Pros

- Enables learning of features rather than hand tuning
- Impressive performance gains
 - Computer vision
 - Speech recognition
 - Some text analysis
- Potential for more impact

Cons

- Requires a lot of data for high accuracy
- Computationally really expensive
- Extremely hard to tune
 - Choice of architecture
 - Parameter types
 - Hyperparameters
 - Learning algorithm
 - ...

Computational cost+ so many choices

=

incredibly hard to tune

Deep features:

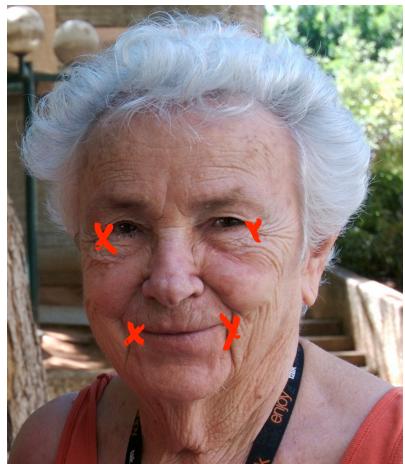
Deep learning

+

Transfer learning

Standard image classification approach

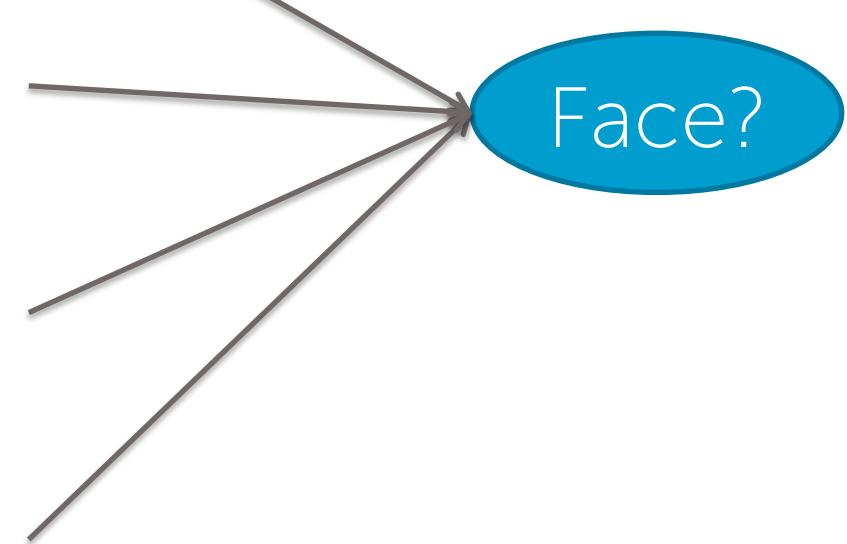
Input



Extract features

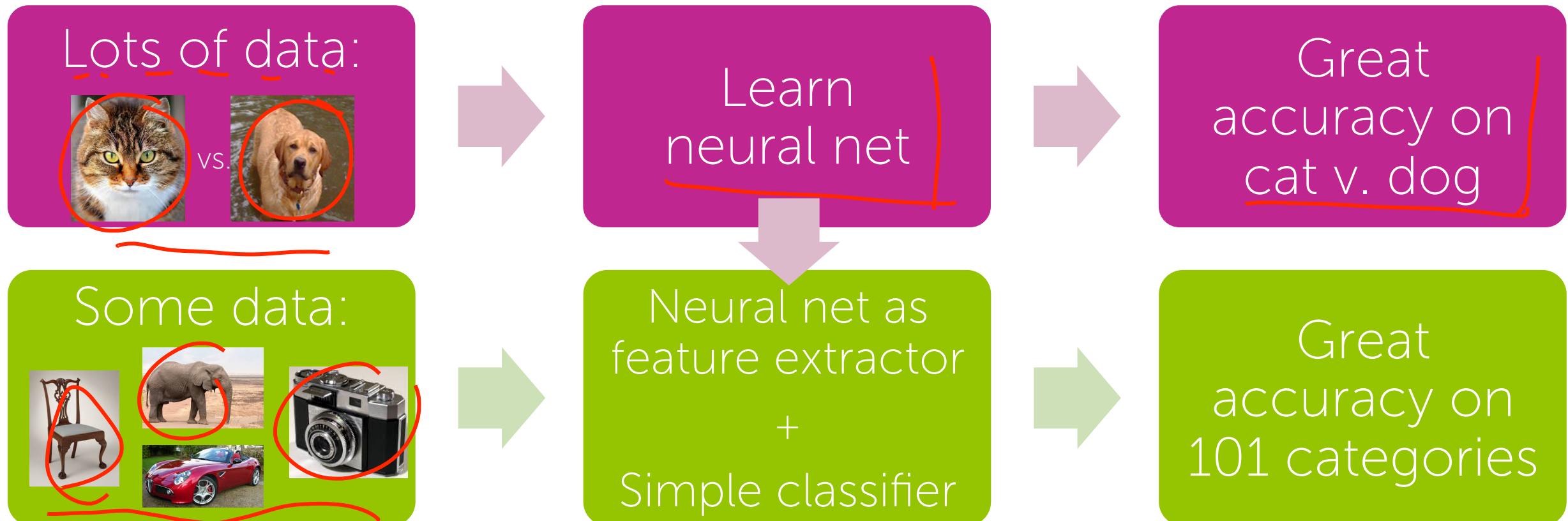
Can we learn
features from
data, even when
we don't have
data or time?

Use simple classifier
e.g., logistic regression, SVMs



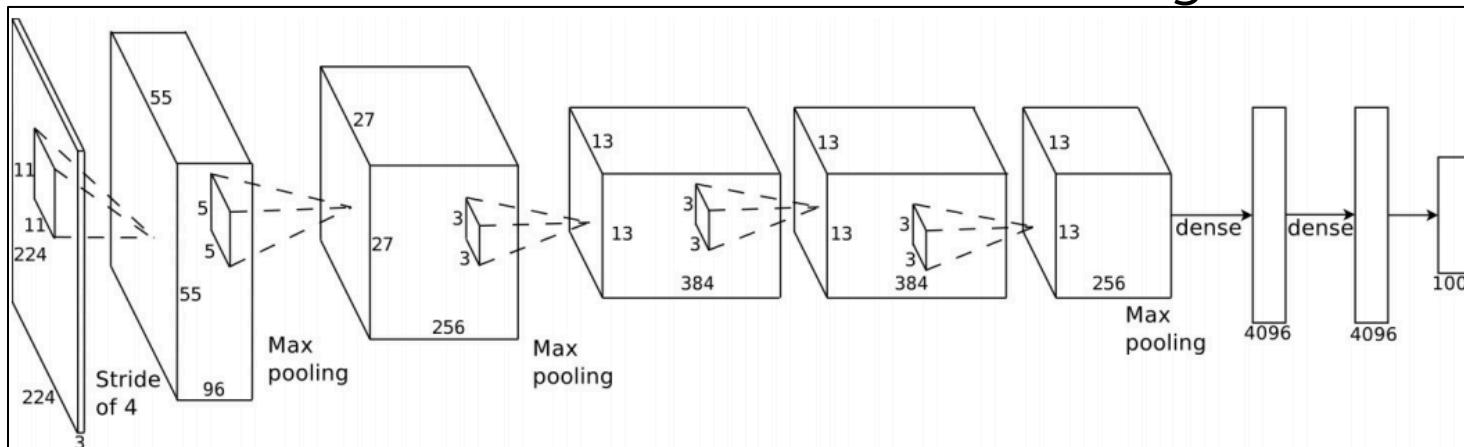
Transfer learning: Use data from one task to help learn on another

Old idea, explored for deep learning by Donahue et al. '14 & others



What's learned in a neural net

Neural net trained for Task 1: cat vs. dog

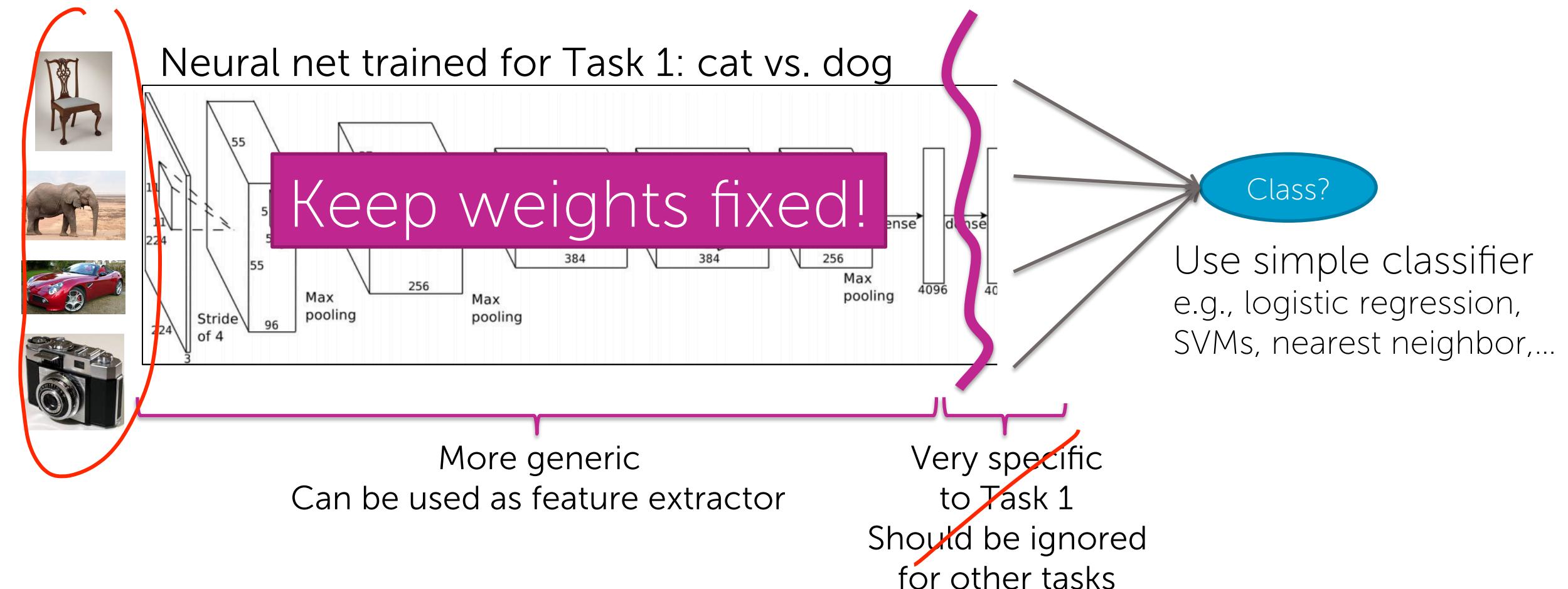


More generic
Can be used as feature extractor

Very specific
to Task 1
Should be ignored
for other tasks

Transfer learning in more detail...

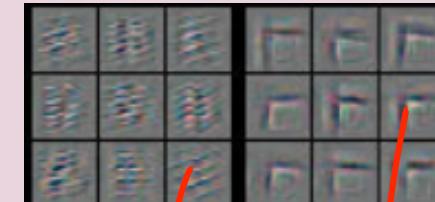
For Task 2, predicting 101 categories,
learn only end part of neural net



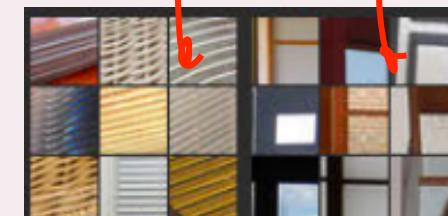
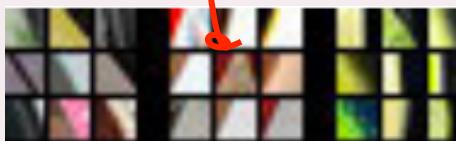
Careful where you cut: *latter layers may be too task specific*



Example
detectors
learned

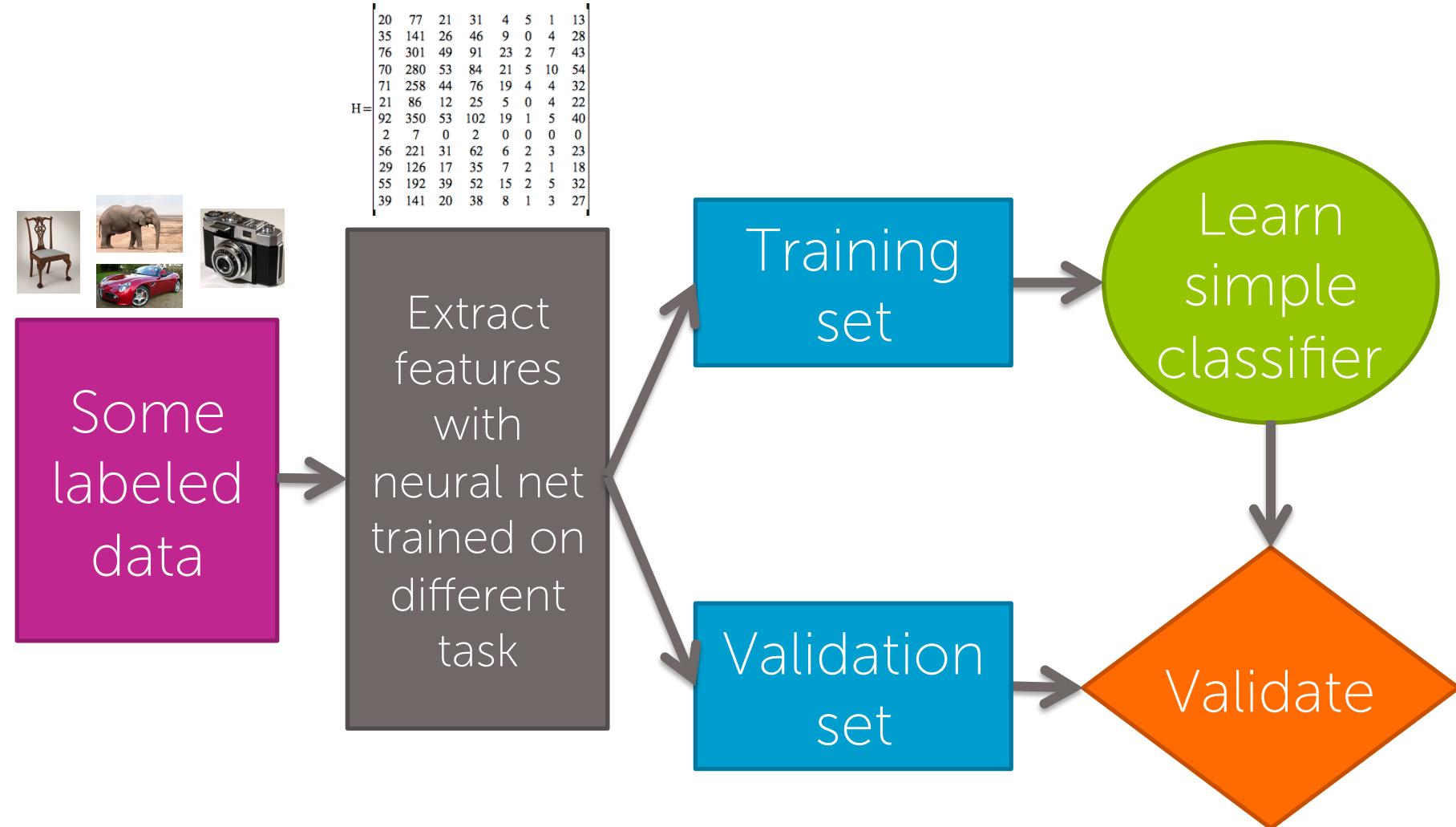


Example
interest
points
detected



[Zeiler & Fergus '13]

Transfer learning with deep features workflow



How general are deep features?

comology



Summary of deep learning

What you can do now...

- Describe multi-layer neural network models
- Interpret the role of features as local detectors in computer vision
- Relate neural networks to hand-crafted image features
- Describe some settings where deep learning achieves significant performance boosts
- State the pros & cons of deep learning model
- Apply the notion of transfer learning
- Use neural network models trained in one domain as features for building a model in another domain
- Build an image retrieval tool using deep features