Deep Learning:

Searching for Images

Emily Fox & Carlos Guestrin

Machine Learning Specialization

University of Washington

Visual product recommender

I want to buy new shoes, but…

Too many options online…

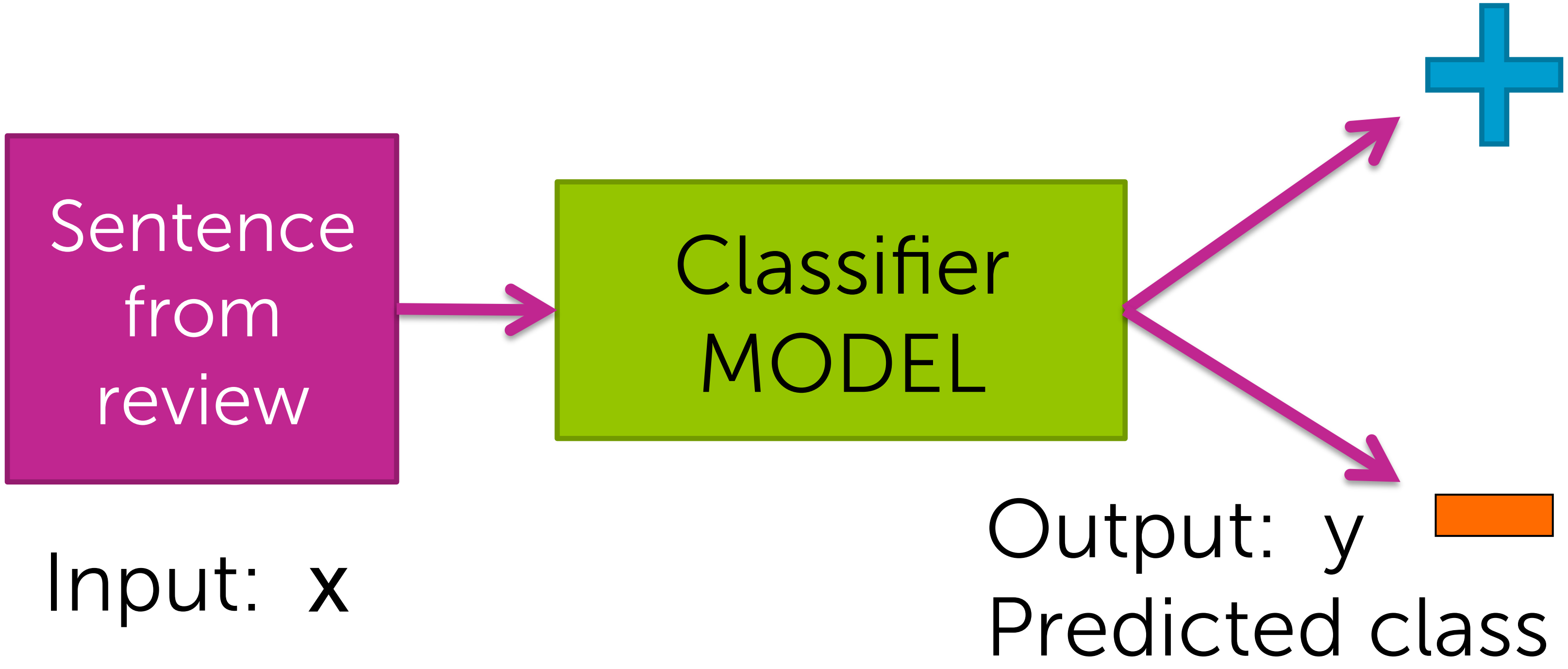
Text search doesn't help...

"Dress shoes"

Visual product search demo

Features are key to machine learning

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



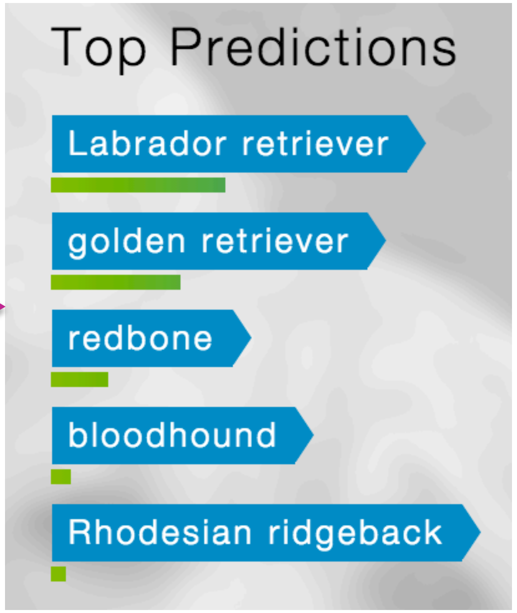
Sentence from review

Classifier MODEL

Input: x

Output: y
Predicted class

Image classification



Top Predictions

- Labrador retriever
- golden retriever
- redbone
- bloodhound
- Rhodesian ridgeback

Input: x

Image pixels

Output: y

Predicted object

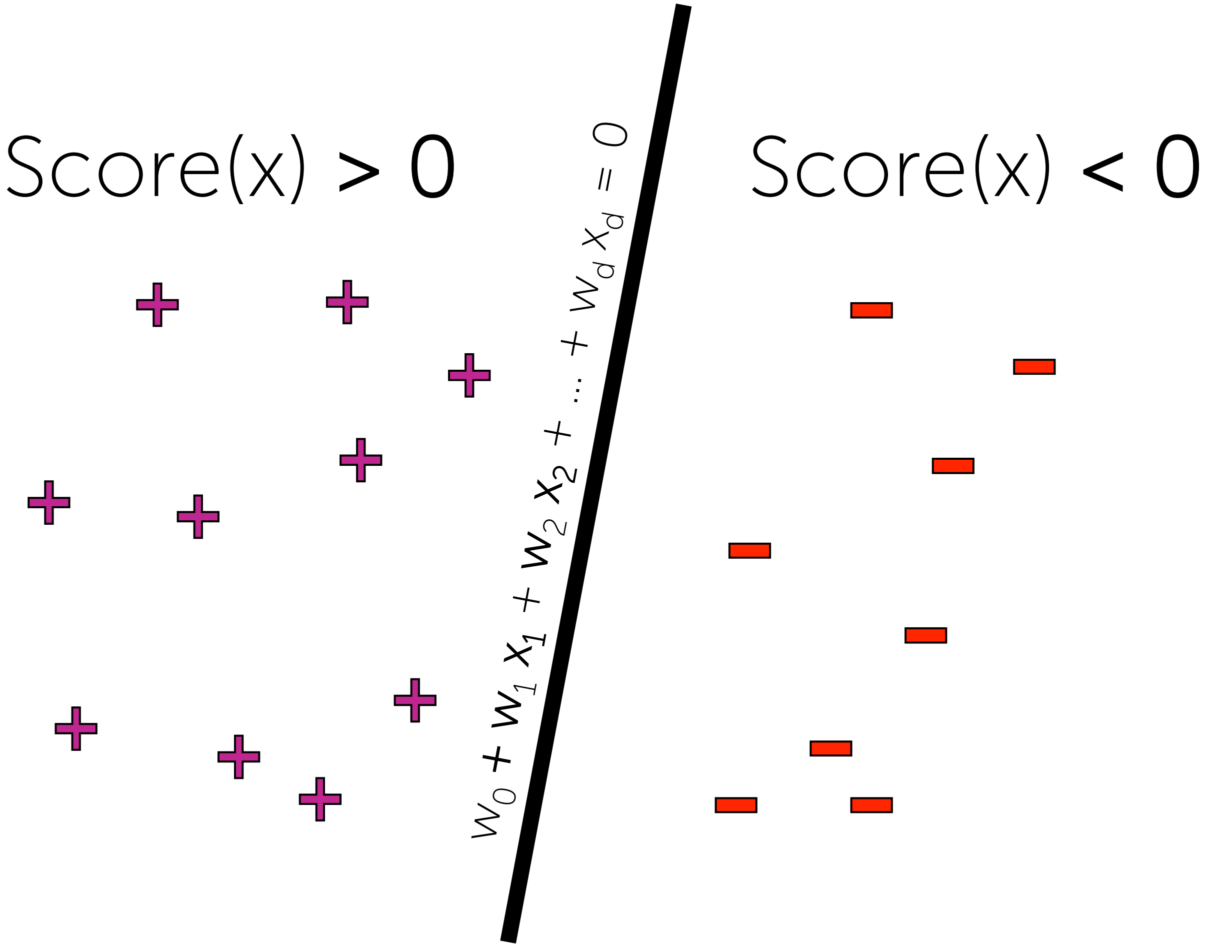
Neural networks

↓

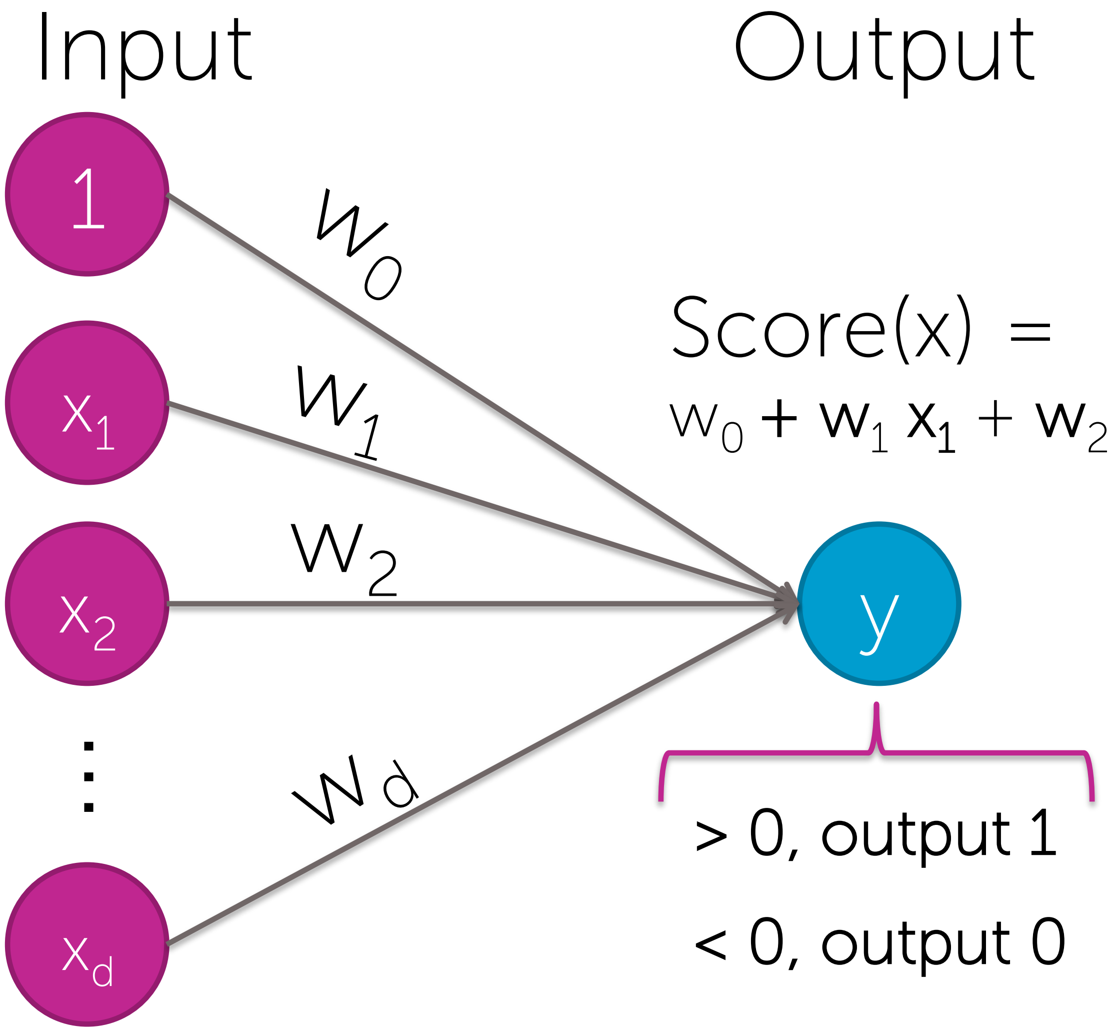
Learning *very* non-linear features

Linear classifiers

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



Graph representation of classifier: useful for defining neural networks



Score(x) =

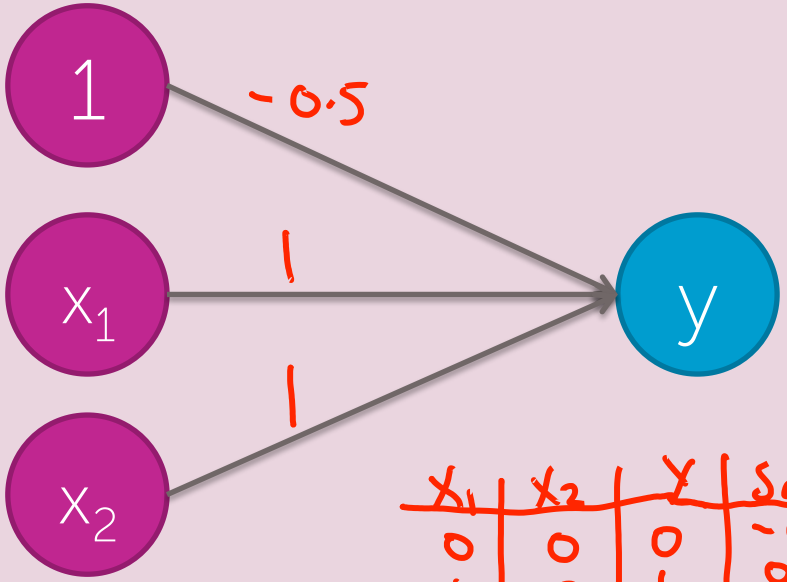
$w_0 + w_1 x_1 + w_2 x_2 + \ldots + w_d x_d$

> 0, output 1

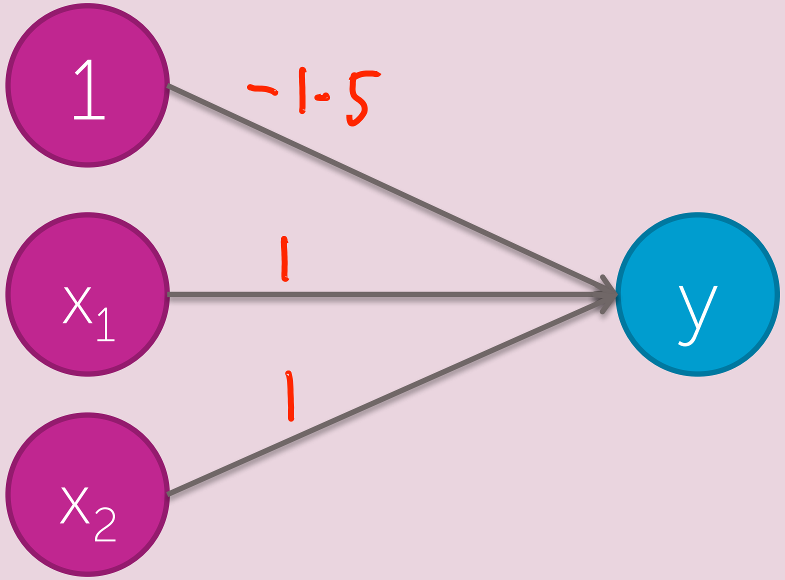
< 0, output 0

What can a linear classifier represent?

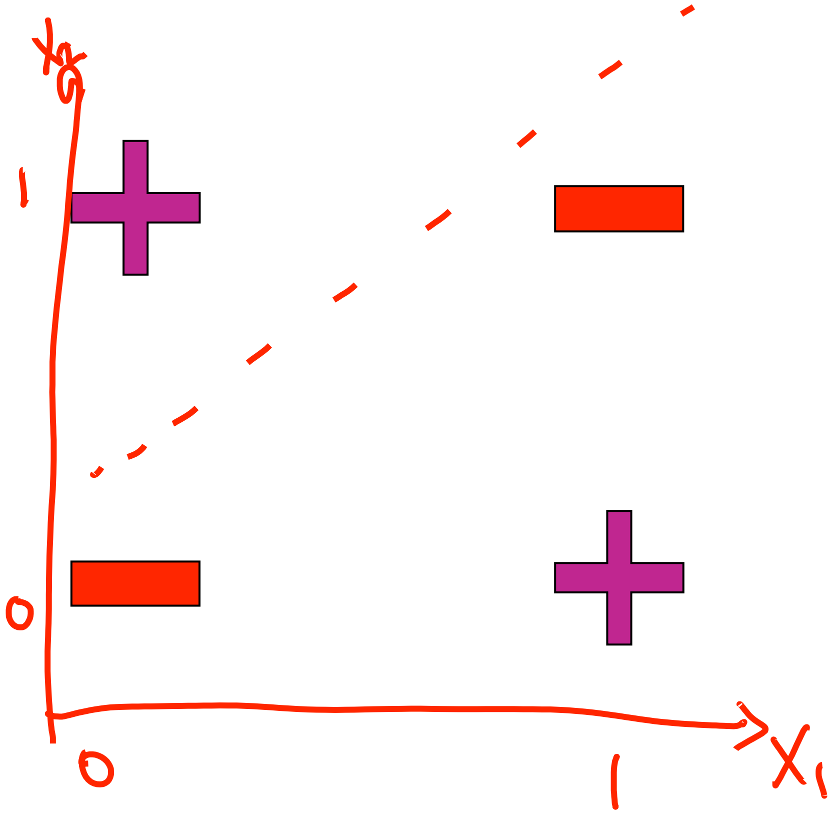
x_1 OR x_2	x_1 AND x_2



x_1	x_2	y	Score
0	0	0	-0.5
1	0	1	0.5
0	1	1	0.5
1	1	1	1.5



What can't a simple linear classifier represent?

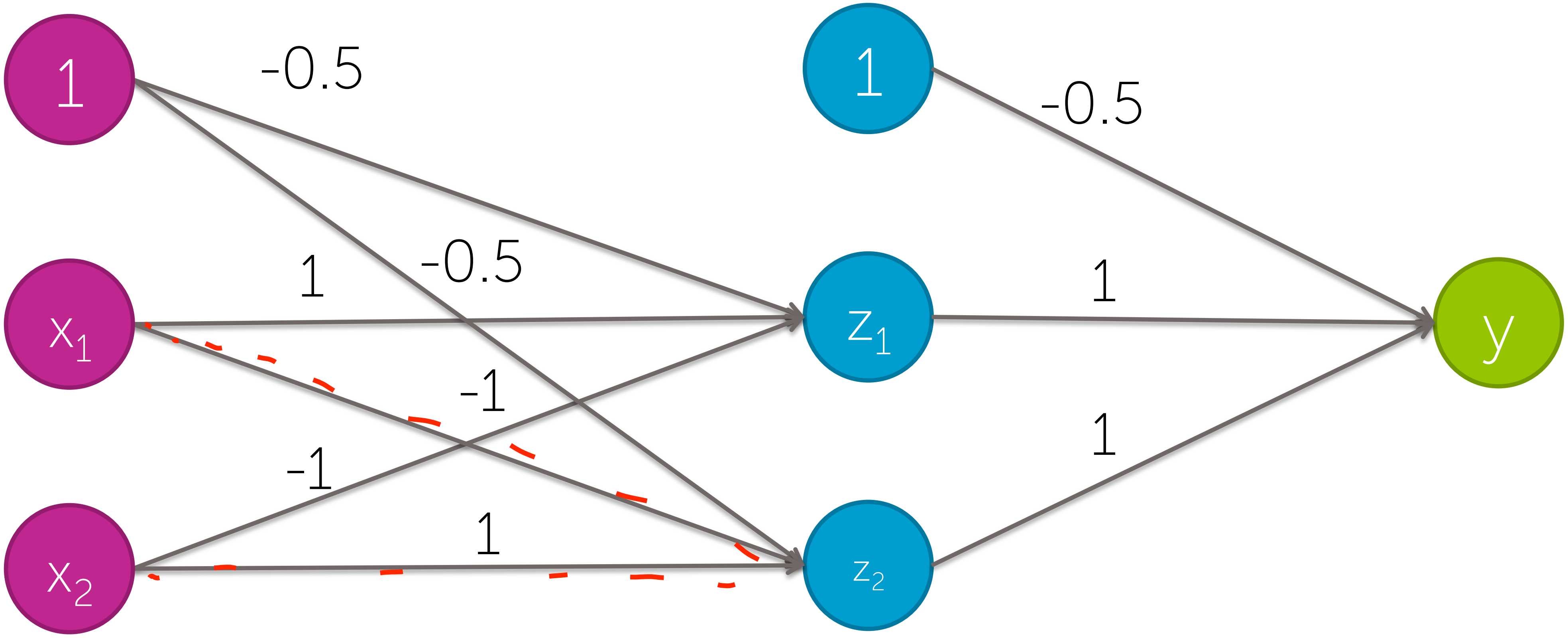


XOR
the counterexample to everything

Need non-linear features

Solving the XOR problem: Adding a layer

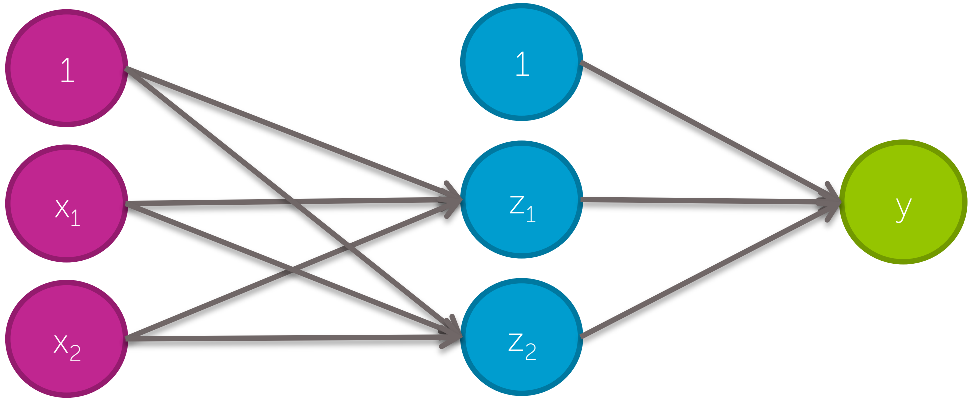
$$\text{XOR} = \underbrace{x_1 \text{ AND NOT } x_2}_{z_1} \text{ OR } \underbrace{\text{NOT } x_1 \text{ AND } x_2}_{z_2}$$



Thresholded to 0 or 1

A neural network

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

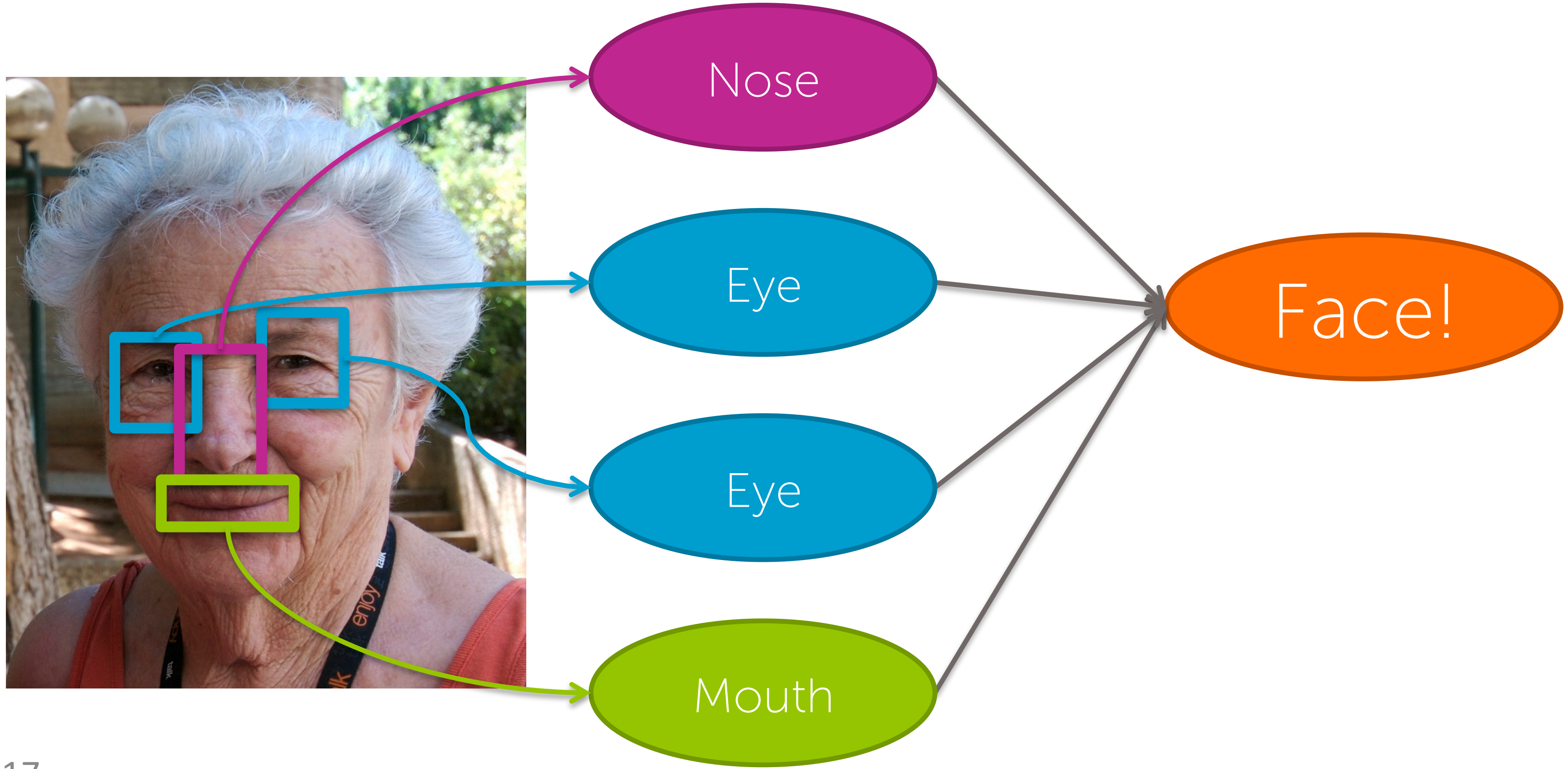


- Around for about 50 years
  - Fell in “disfavor” in 90s
- In last few years, big resurgence
  - Impressive accuracy on several benchmark problems
  - Powered by huge datasets, GPUs, & modeling/learning alg improvements

Application of deep learning to computer vision

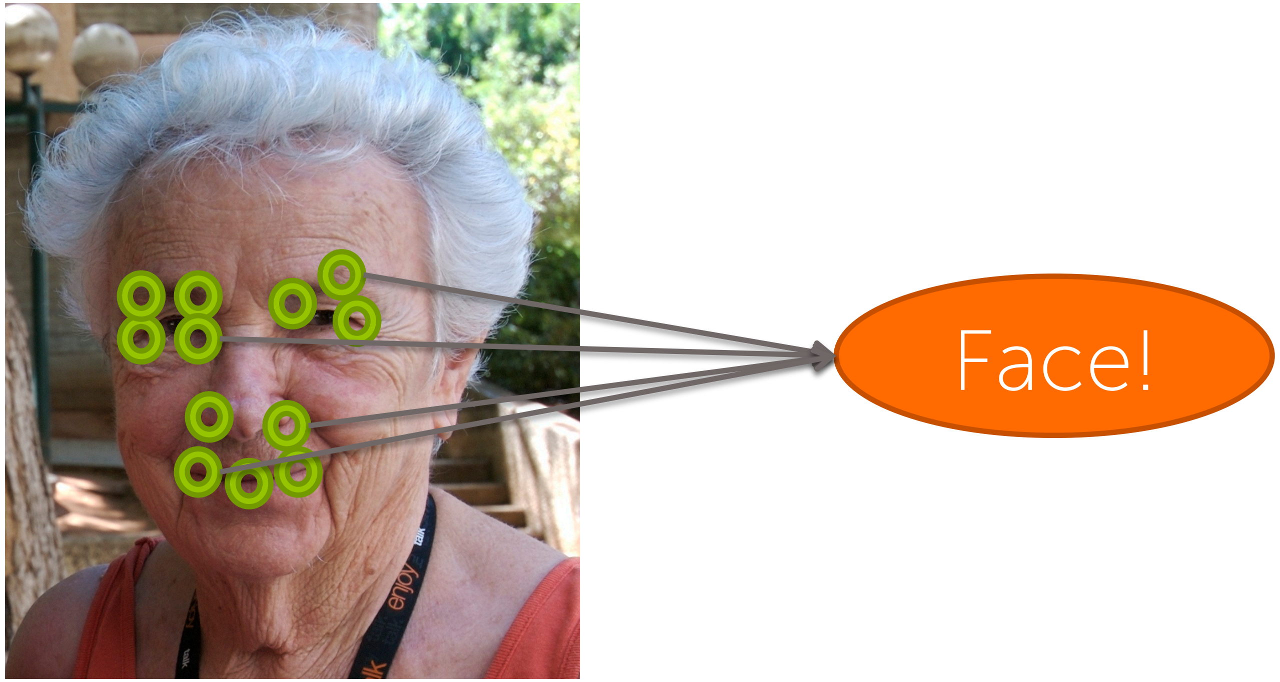
Image features

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

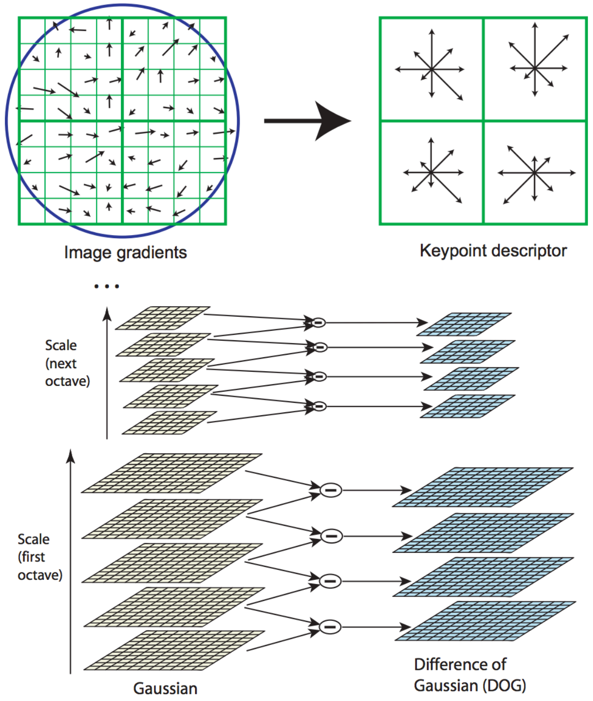


Typical local detectors look for locally "interesting points" in image

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



Many hand created features exist for finding interest points…

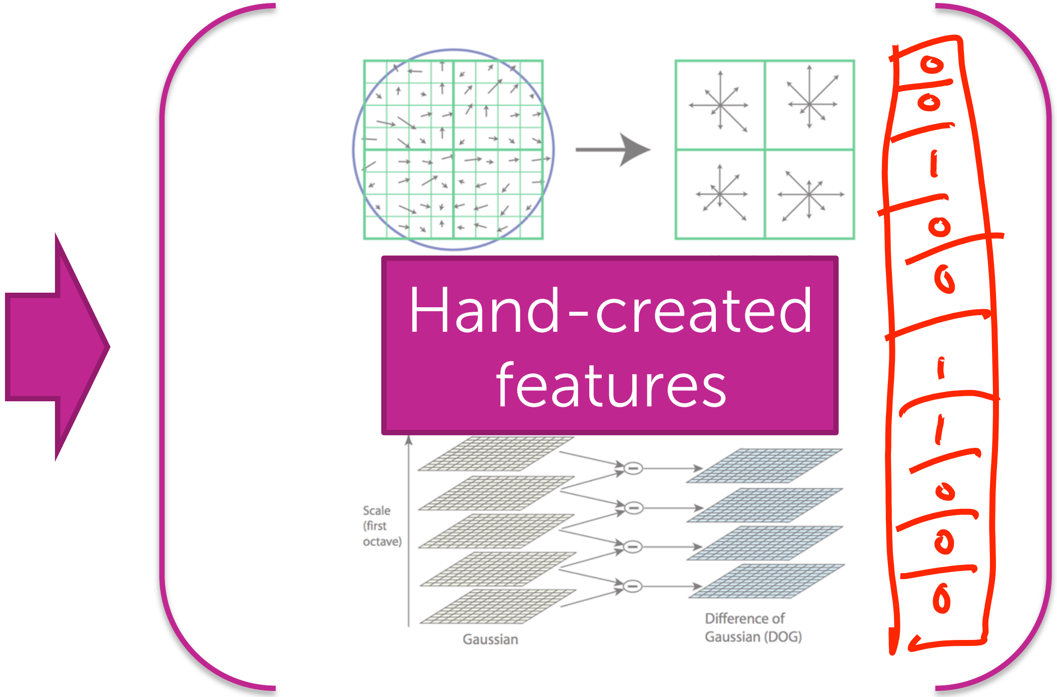


SIFT [Lowe '99]

- *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

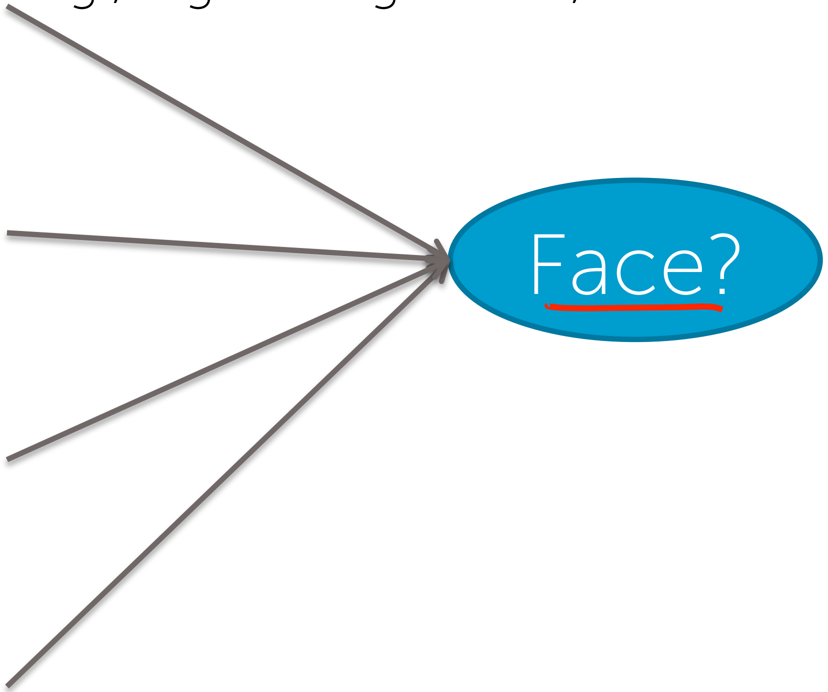


Extract features

Hand-created features

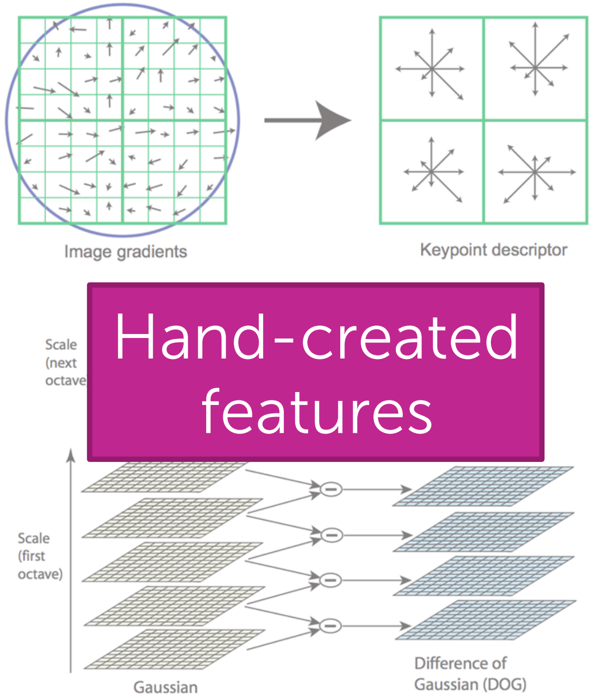
Use simple classifier

e.g., logistic regression, SVMs



Face?

Many hand created features exist for finding interest points…



Hand-created features

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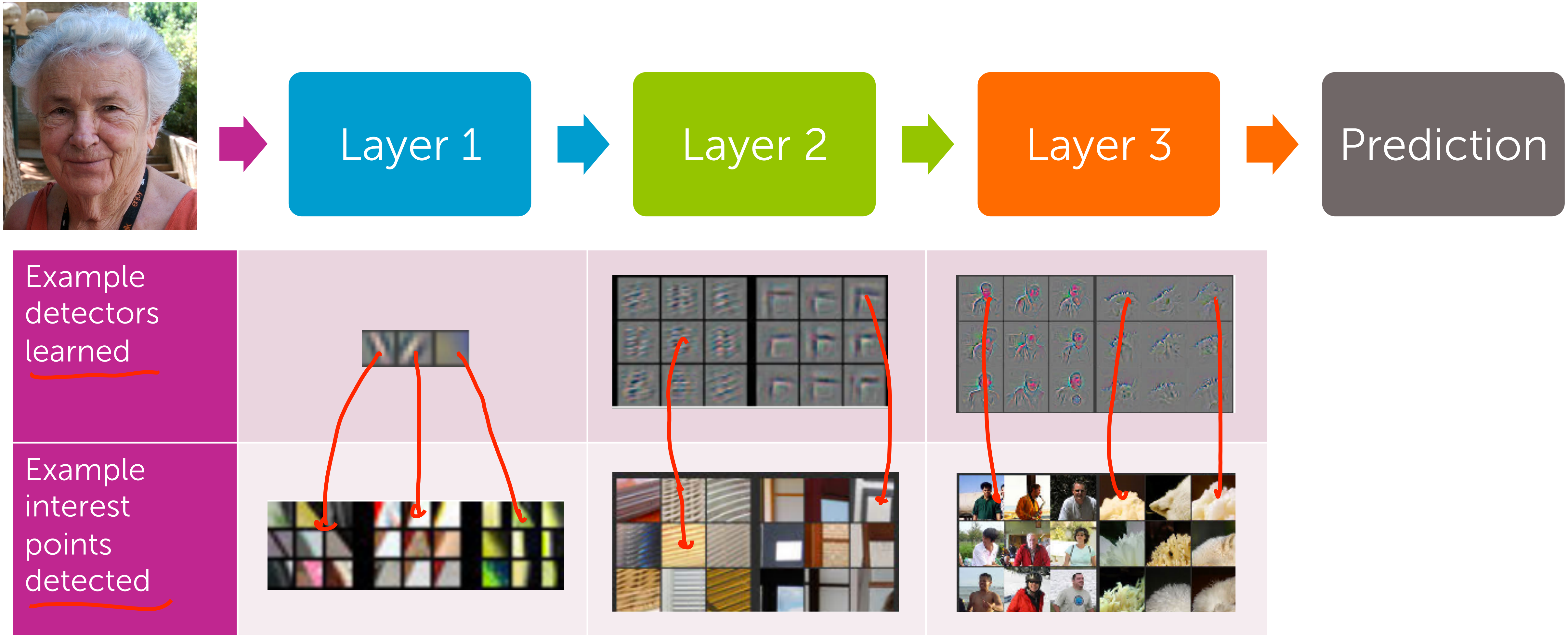
- …

… but very painful to design

Deep learning:
implicitly learns features



Layer 1

Layer 2

Layer 3

Prediction

Example detectors learned

Example interest points detected

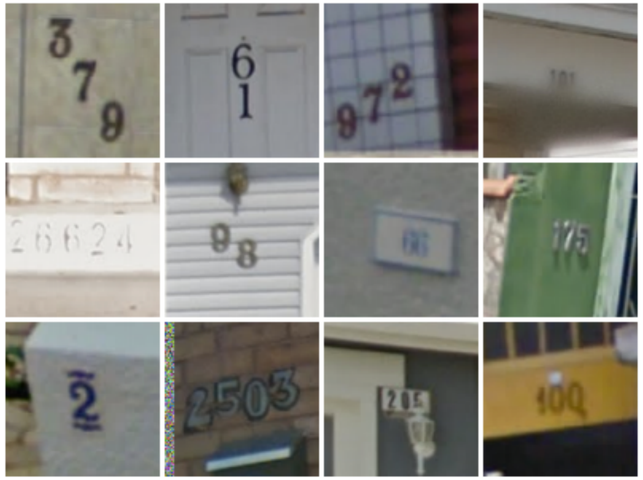
[Zeiler & Fergus '13]

Deep learning performance

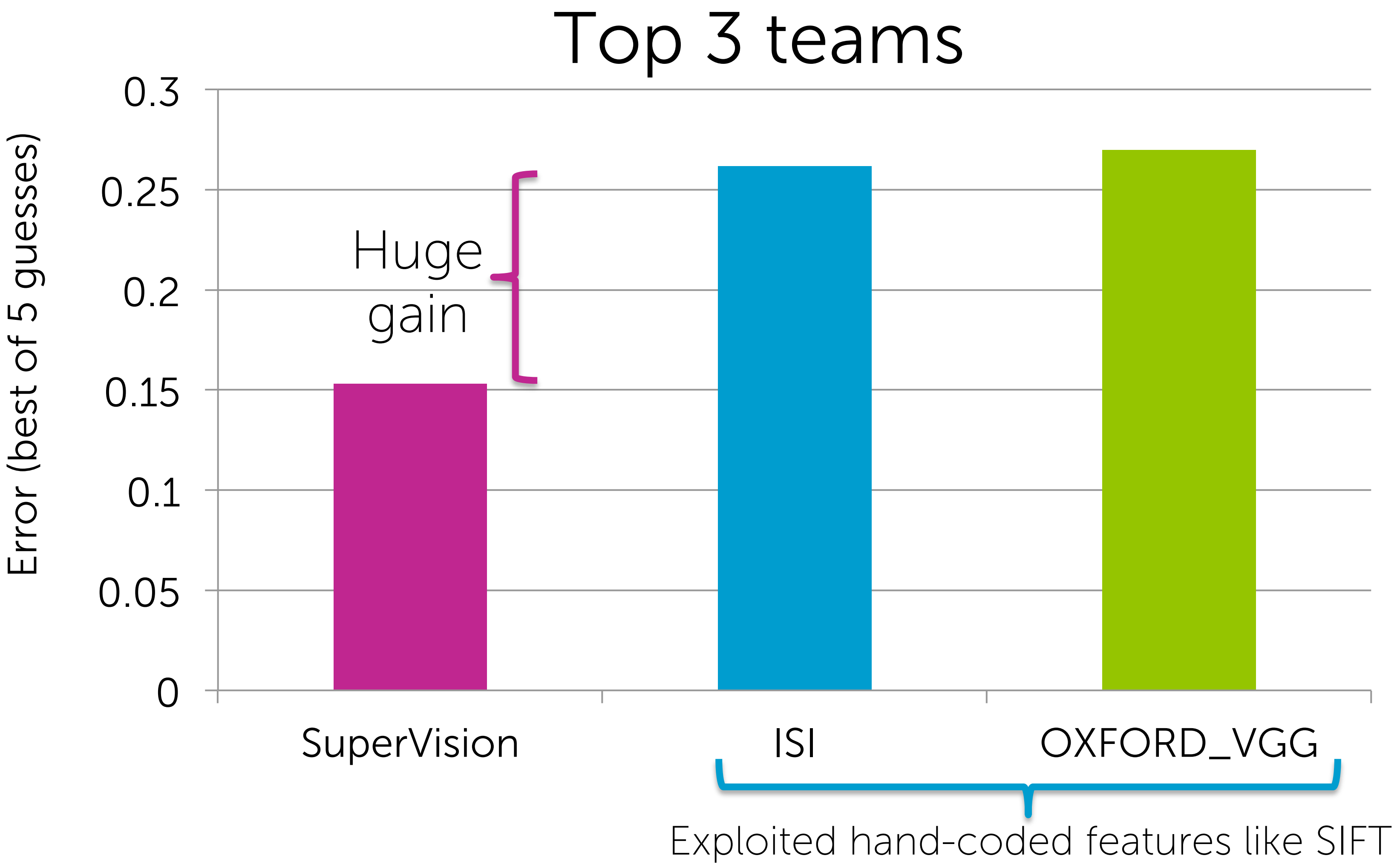
Sample results using deep neural networks

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

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



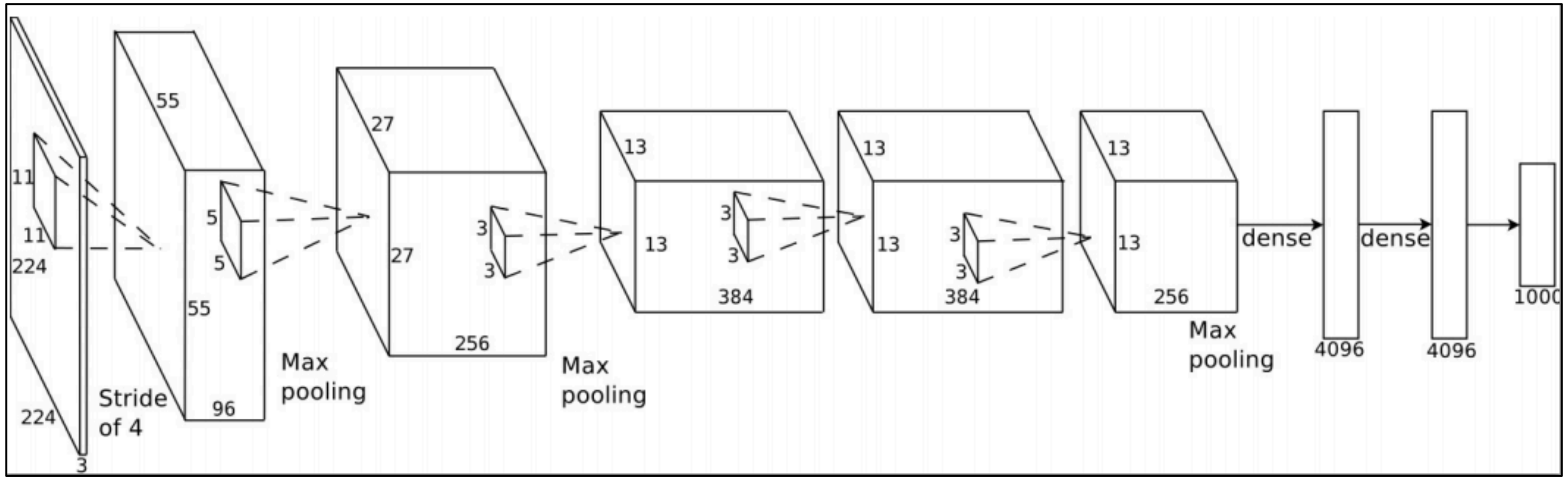
ImageNet 2012 competition: 1.2M training images, 1000 categories



Exploited hand-coded features like SIFT

ImageNet 2012 competition: 1.2M training images, 1000 categories

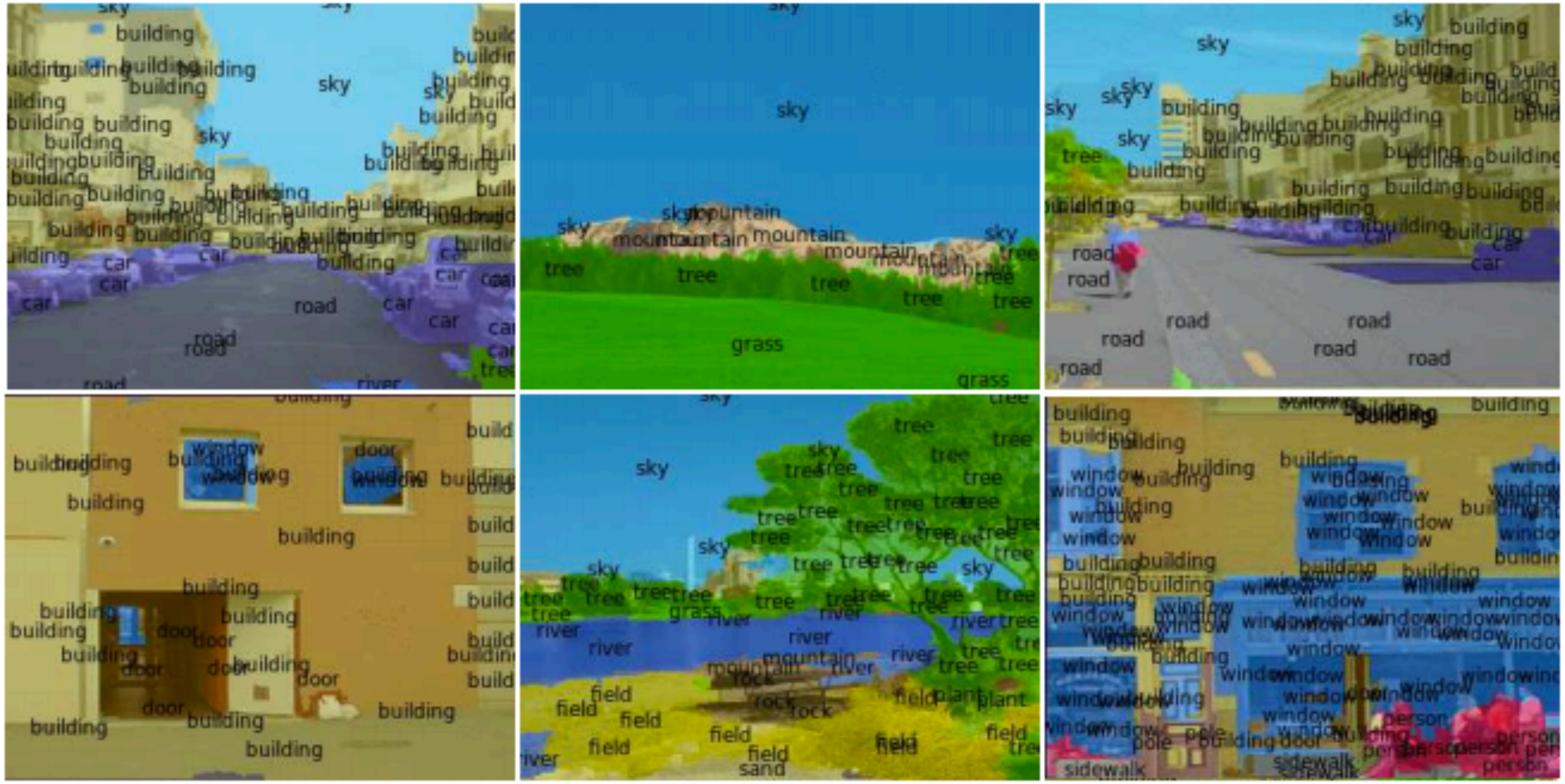
Winning entry: SuperVision
8 layers, 60M parameters [Krizhevsky et al. '12]



Achieving these amazing results required:
- New learning algorithms
- GPU implementation

Deep learning in computer vision

Scene parsing with deep learning

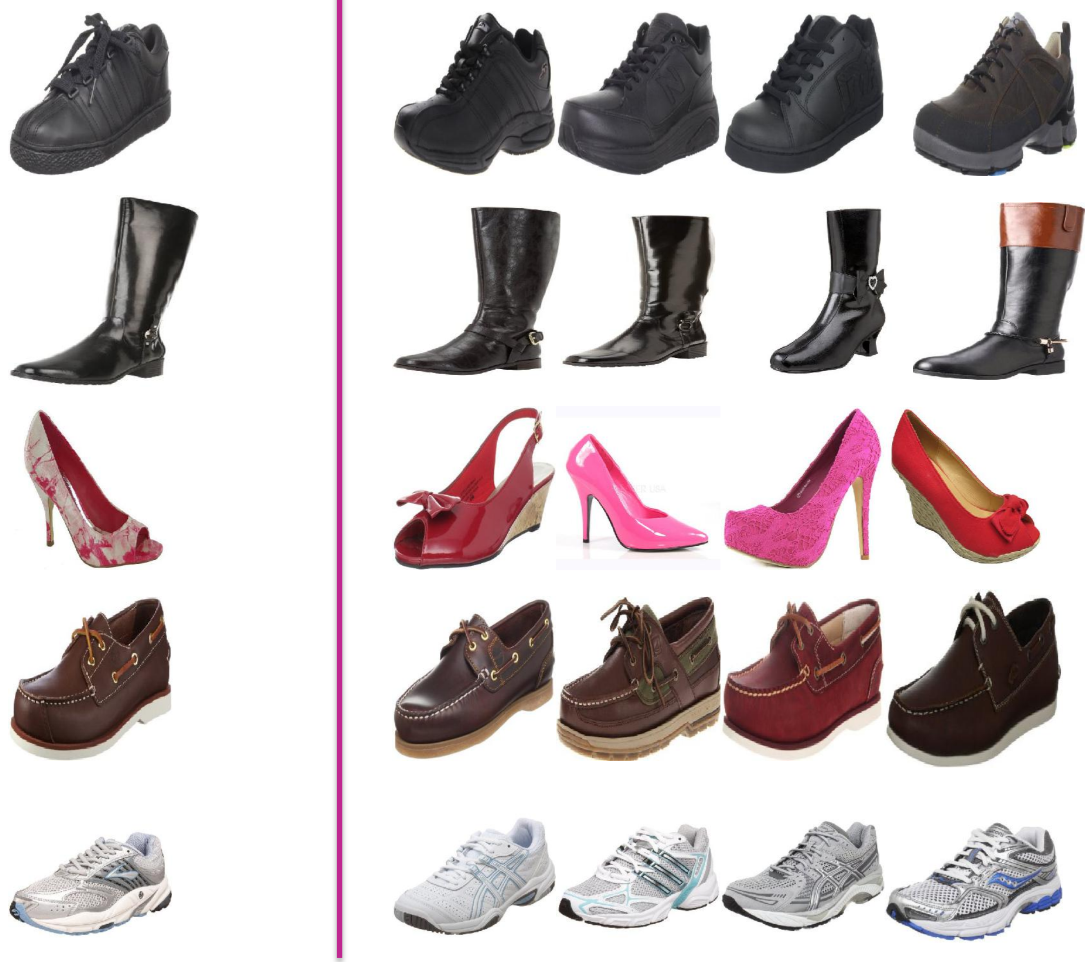


[Farabet et al. '13]

Retrieving similar images

Input Image

Nearest neighbors



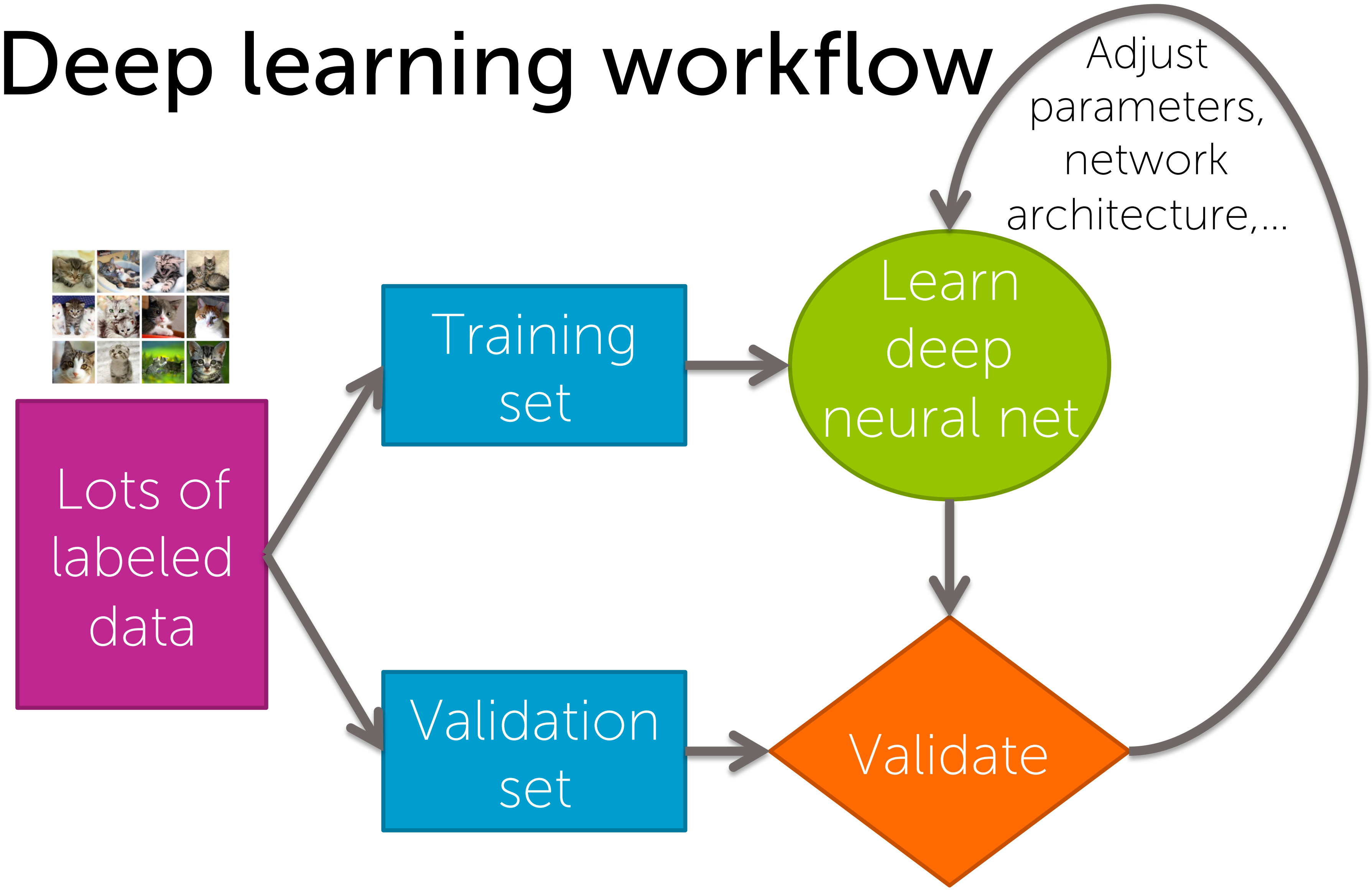
Challenges of deep learning

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



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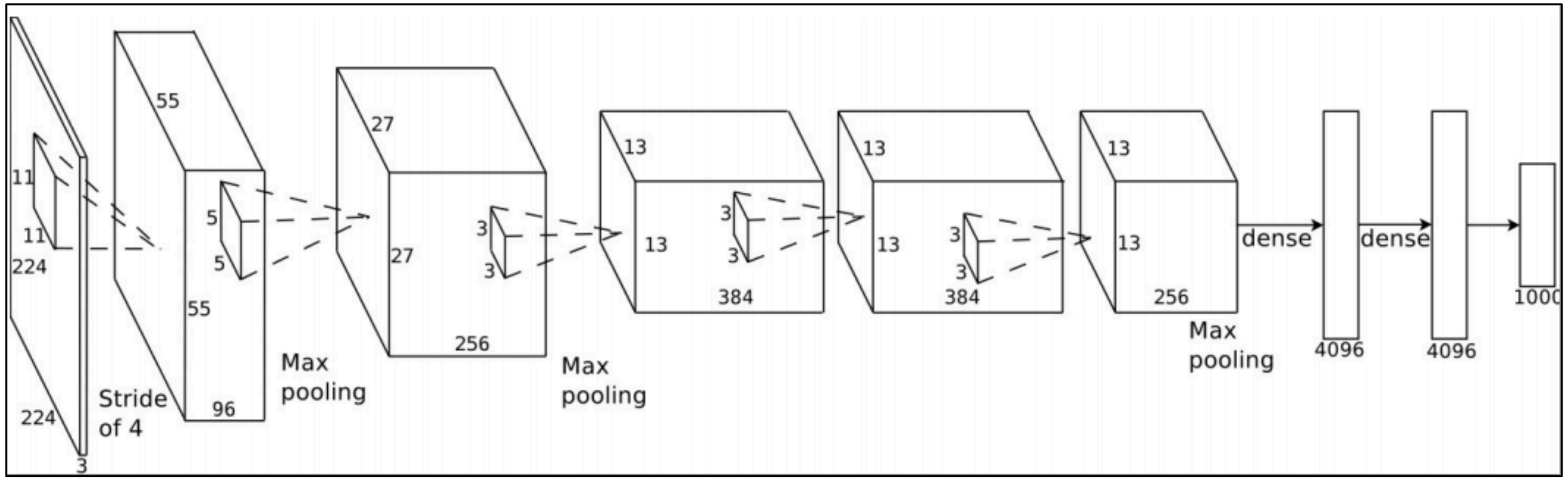
Many tricks needed to work well…

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

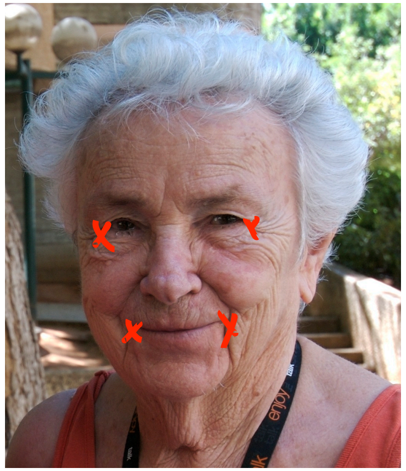
Standard image classification approach

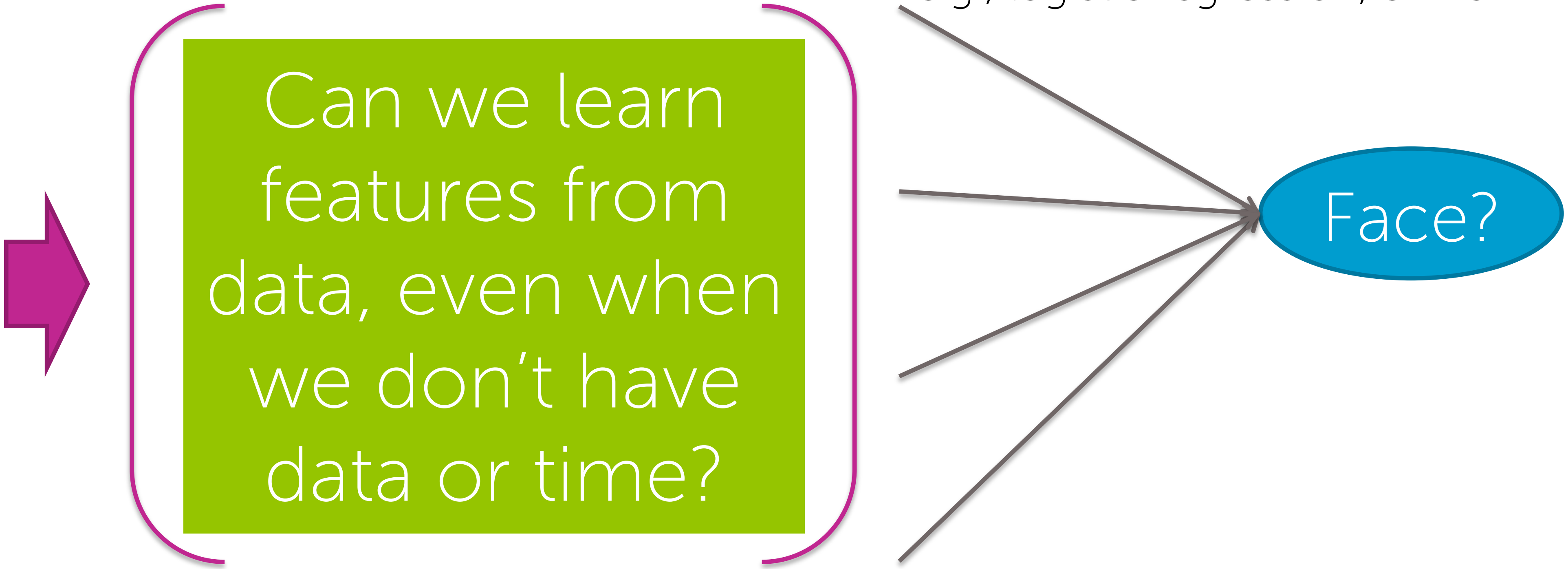
Input

Extract features

Use simple classifier

e.g., logistic regression, SVMs

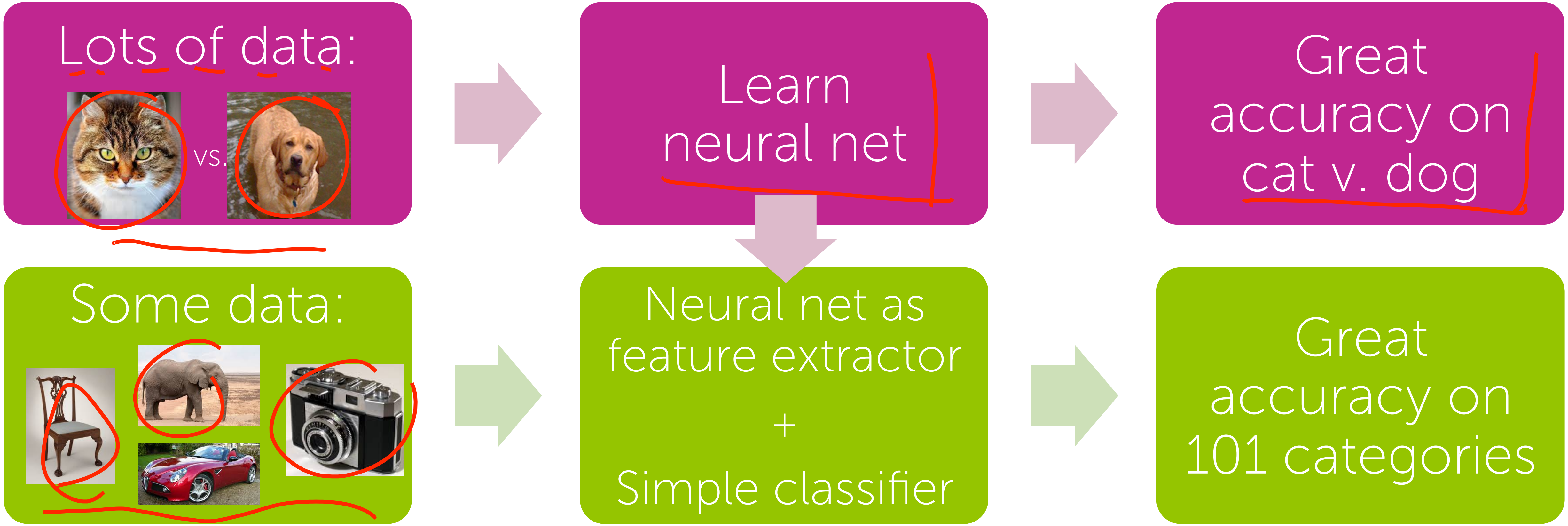




Can we learn features from data, even when we don't have data or time?

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

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



Lots of data:

vs.

Learn neural net

Great accuracy on cat v. dog

Some data:

Neural net as feature extractor

+

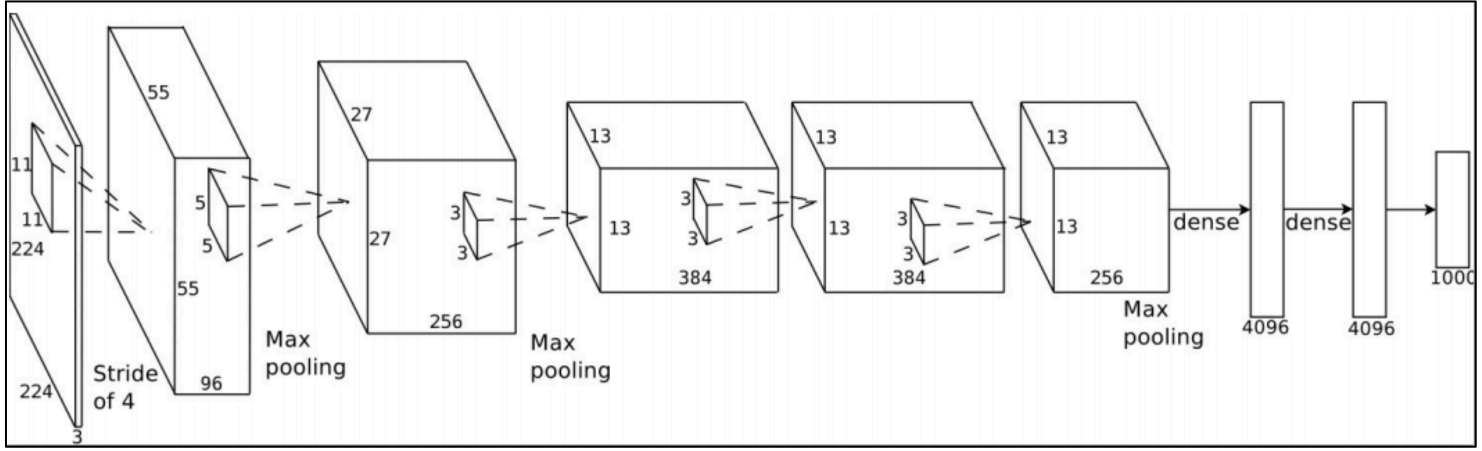
Simple classifier

Great accuracy on 101 categories

What's learned in a neural net

VS.

Neural net trained for Task 1: cat vs. dog

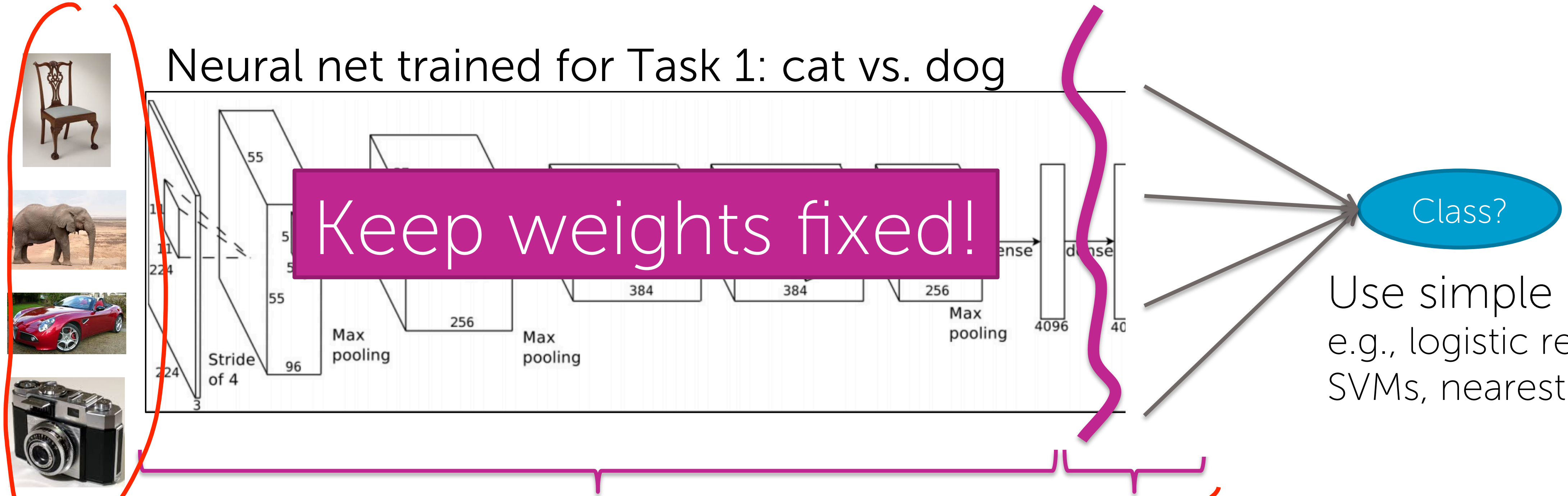


More generic
Can be used as feature extractor

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



Neural net trained for Task 1: cat vs. dog

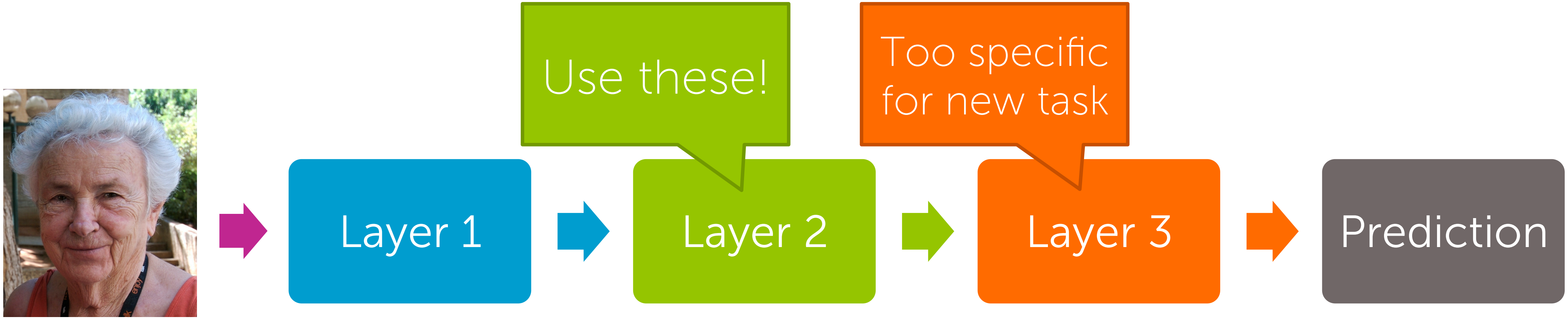
Keep weights fixed!

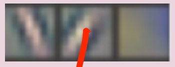
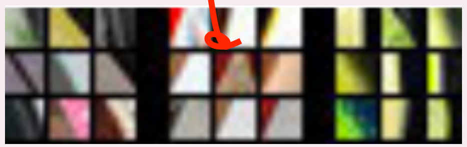
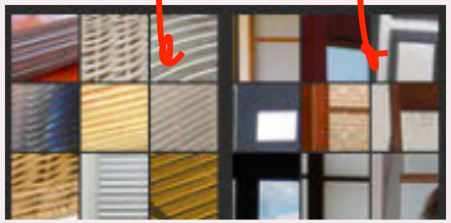
Use simple classifier
e.g., logistic regression, SVMs, nearest neighbor,…

More generic
Can be used as feature extractor

~~Very specific to Task 1
Should be ignored for other tasks~~

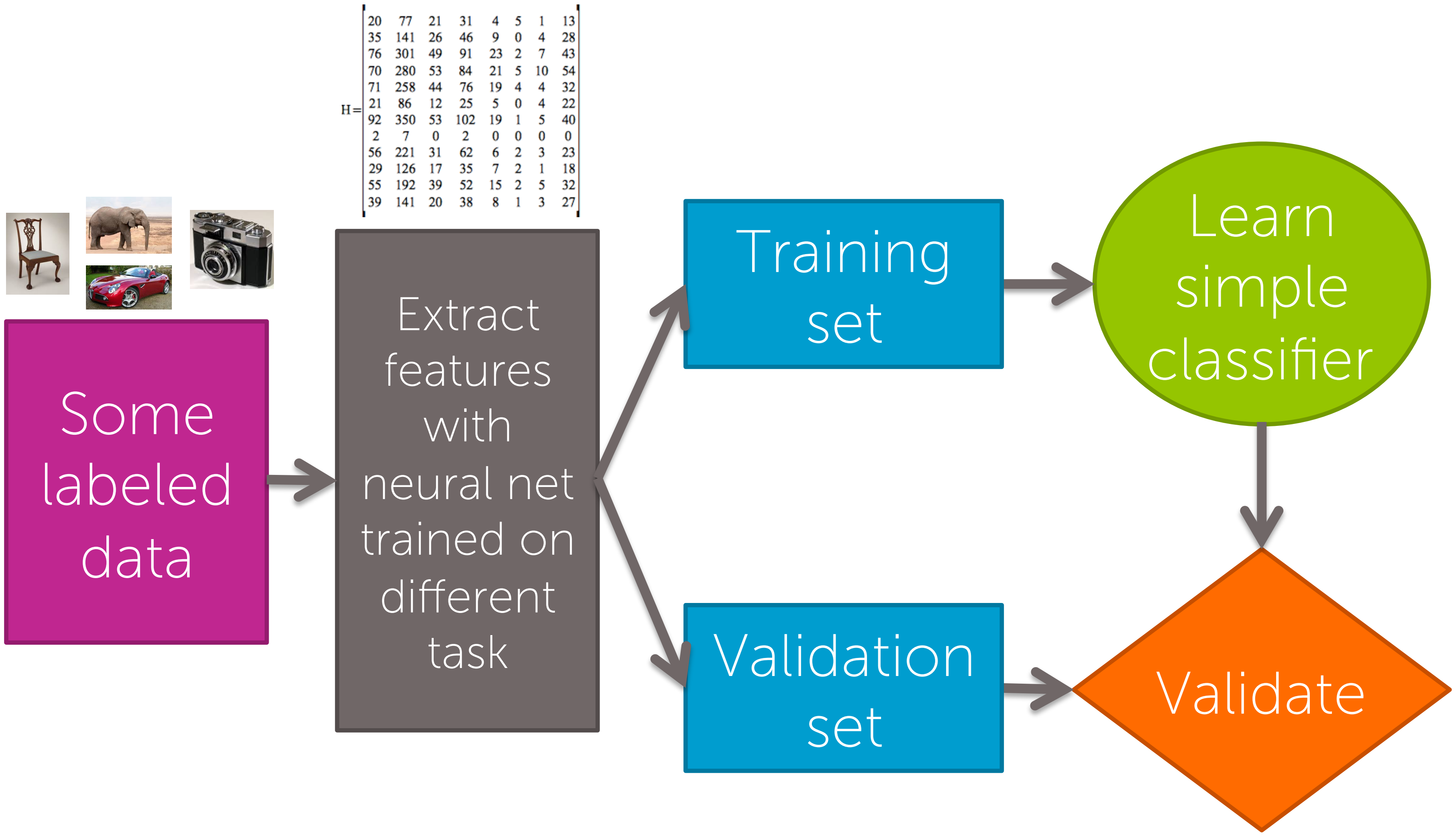
Careful where you cut:
latter layers may be too task specific



Example detectors learned			
Example interest points detected			

[Zeiler & Fergus '13]

Transfer learning with deep features workflow



$$H=\begin{bmatrix} 20 & 77 & 21 & 31 & 4 & 5 & 1 & 13 \\ 35 & 141 & 26 & 46 & 9 & 0 & 4 & 28 \\ 76 & 301 & 49 & 91 & 23 & 2 & 7 & 43 \\ 70 & 280 & 53 & 84 & 21 & 5 & 10 & 54 \\ 71 & 258 & 44 & 76 & 19 & 4 & 4 & 32 \\ 21 & 86 & 12 & 25 & 5 & 0 & 4 & 22 \\ 92 & 350 & 53 & 102 & 19 & 1 & 5 & 40 \\ 2 & 7 & 0 & 2 & 0 & 0 & 0 & 0 \\ 56 & 221 & 31 & 62 & 6 & 2 & 3 & 23 \\ 29 & 126 & 17 & 35 & 7 & 2 & 1 & 18 \\ 55 & 192 & 39 & 52 & 15 & 2 & 5 & 32 \\ 39 & 141 & 20 & 38 & 8 & 1 & 3 & 27 \end{bmatrix}$$

Some labeled data

Extract features with neural net trained on different task

Training set

Validation set

Learn simple classifier

Validate

How general are deep features?

compology

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