Lecture Notes for

Machine Learning in Python

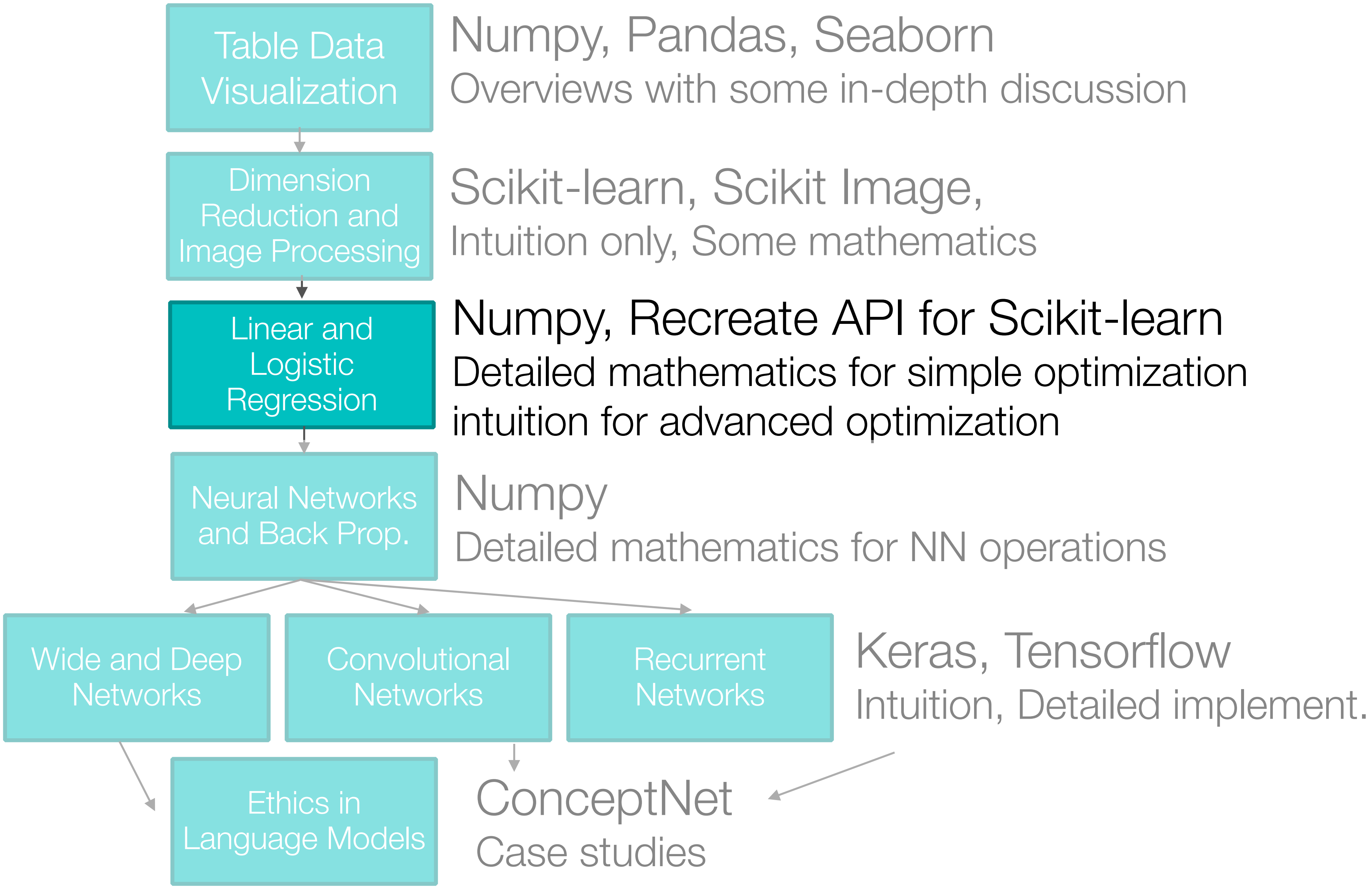
Professor Eric Larson

Logistic Regression

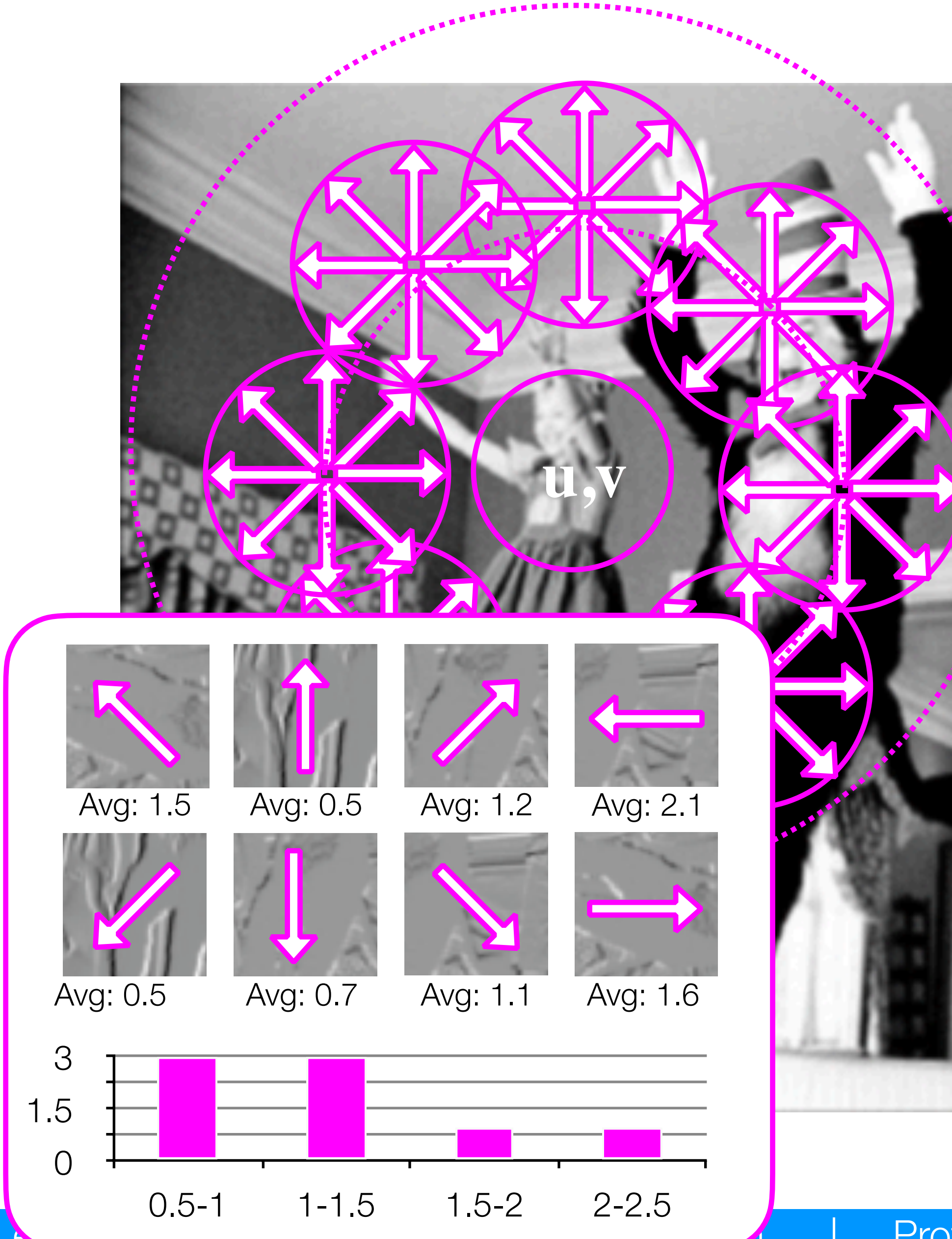
Class Logistics and Agenda

- Logistics
  - A2: Images due soon!
  - Grading update
  - **Reminder**: Stay up to date with the quizzes!
- Agenda
  - Finish Image Town Hall
  - Logistic Regression
    - Solving
    - Programming
    - Finally some object oriented python!

Class Overview, by topic



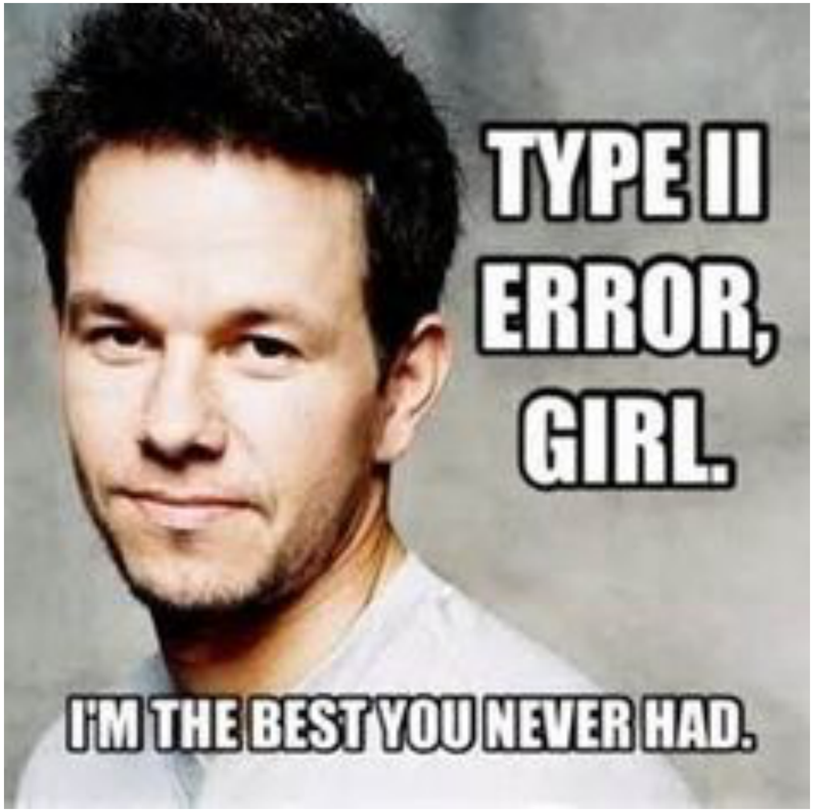
Last Time: DAISY



1. Select u,v pixel location in image
2. Take histogram of average gradient magnitudes in circle for each orientation $\tilde{h}_\Sigma(u, v)$
3. Select circles in a ring, R
4. For each circle on the ring, take another histogram $\tilde{h}_\Sigma(\mathbf{l}_O(u, v, R_1))$
5. Repeat for more rings
6. Save all histograms as "descriptors" $[\tilde{h}_\Sigma(\cdot),\tilde{h}_\Sigma(\cdot),\tilde{h}_\Sigma(\cdot)\ldots]$
7. Can concatenate descriptors as "feature" vector at that pixel location

Town Hall for Lab 2, Images

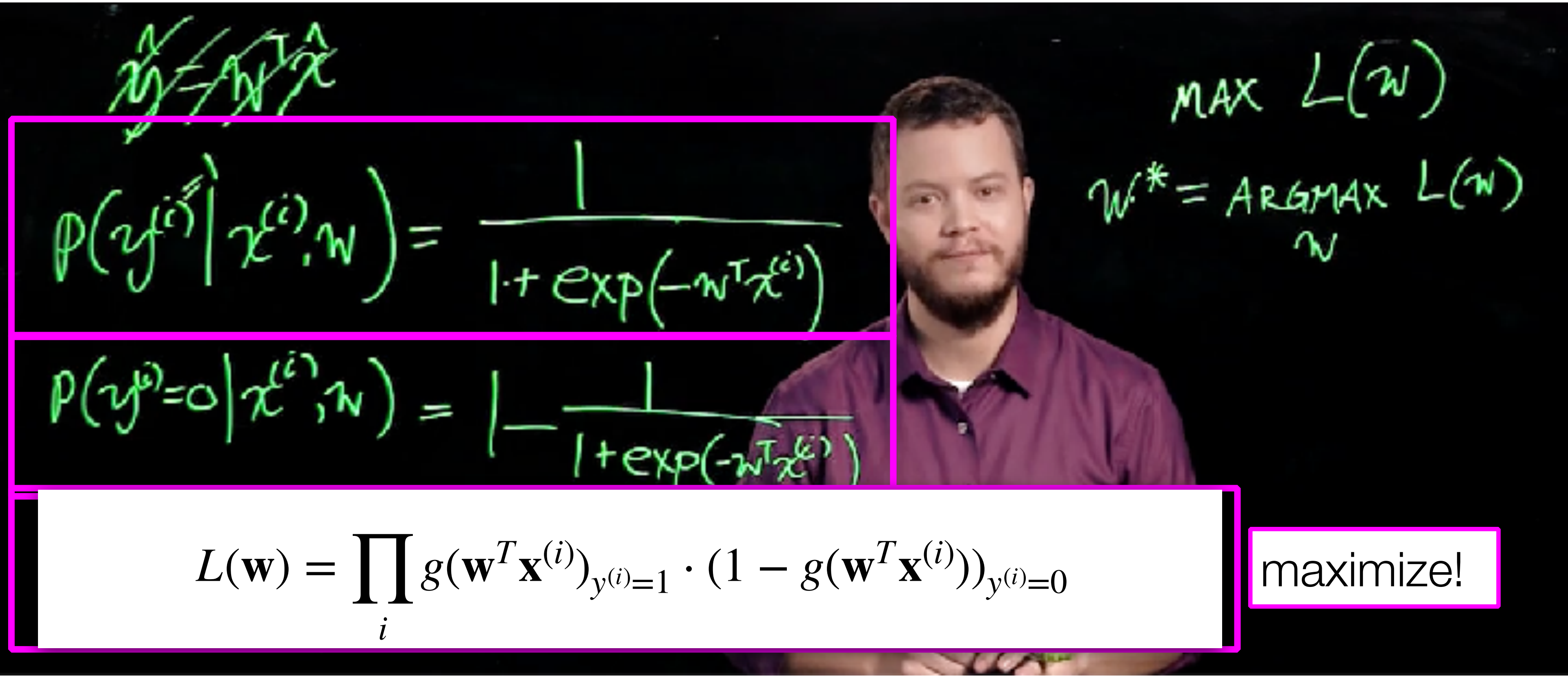
Logistic Regression



@researchmark

Setting Up Binary Logistic Regression

- From flipped lecture:

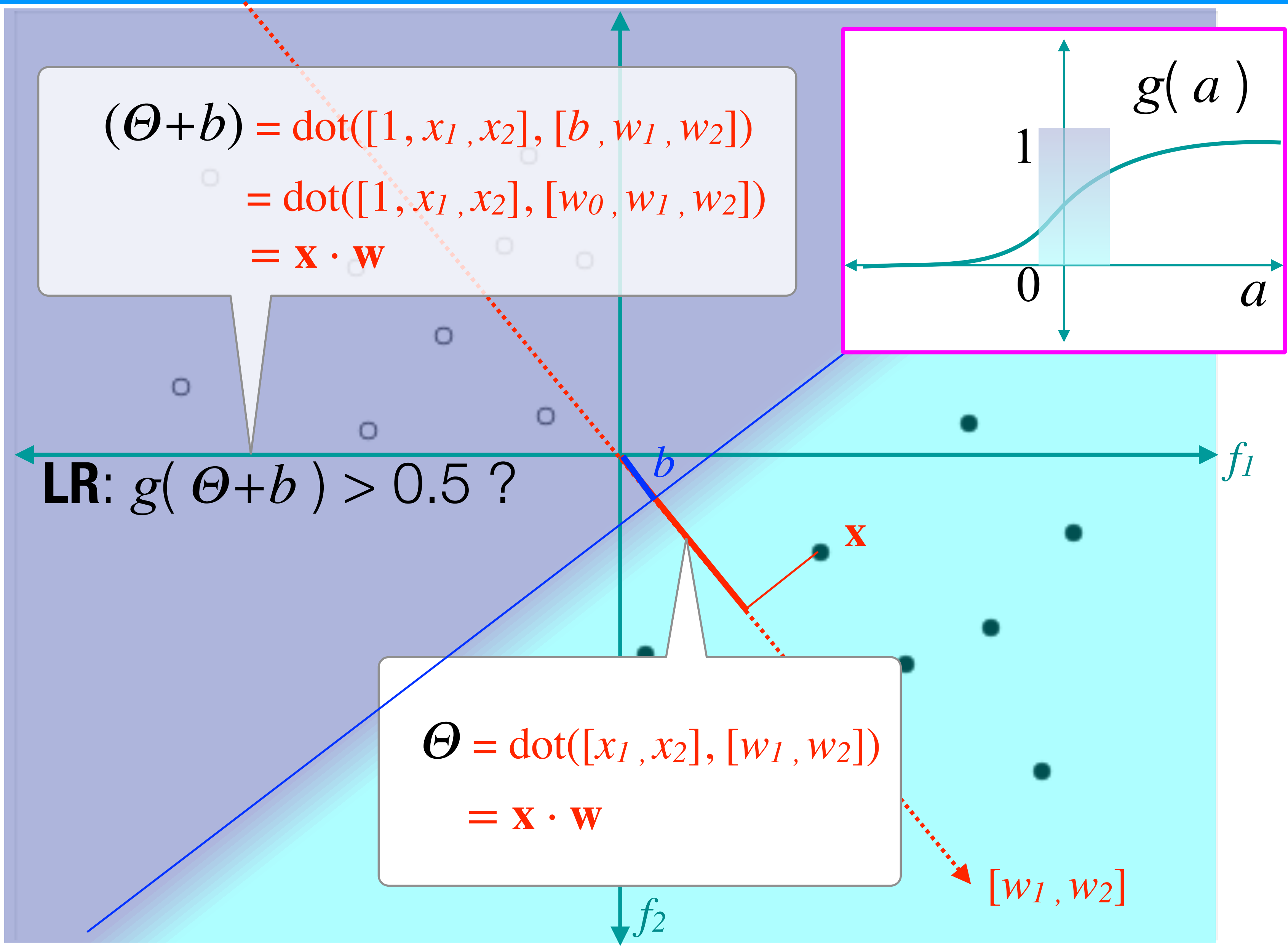


$$L(\mathbf{w}) = \prod_i g(\mathbf{w}^T\mathbf{x}^{(i)})_{y^{(i)}=1} \cdot (1 - g(\mathbf{w}^T\mathbf{x}^{(i)}))_{y^{(i)}=0}$$

maximize!

where $g(.)$ is a sigmoid

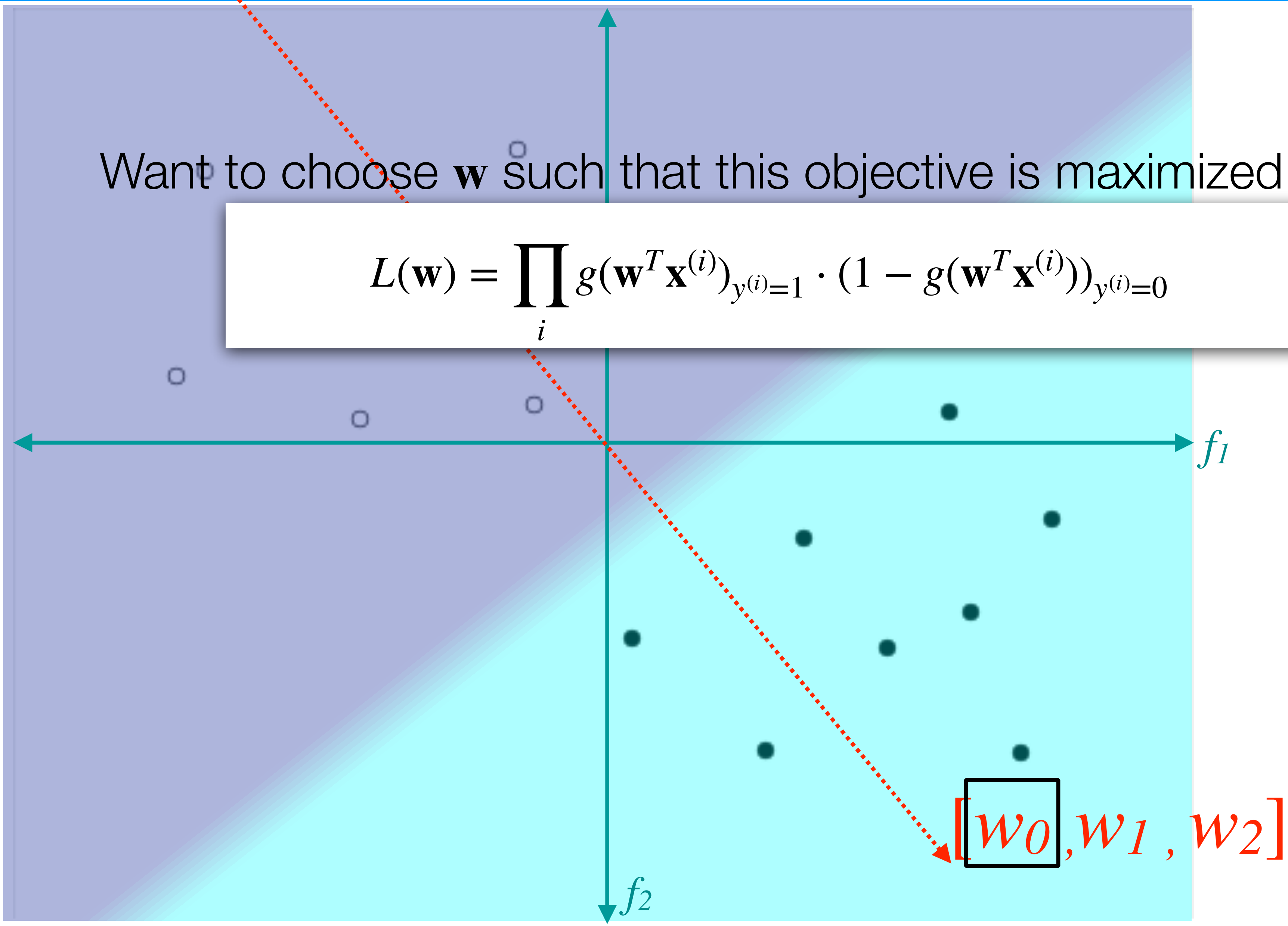
What do weights and intercept define?



Changing $\mathbf{w}$ alters probability

Want to choose $\mathbf{w}$ such that this objective is maximized

$$L(\mathbf{w}) = \prod_i g(\mathbf{w}^T\mathbf{x}^{(i)})_{y^{(i)}=1} \cdot (1 - g(\mathbf{w}^T\mathbf{x}^{(i)}))_{y^{(i)}=0}$$



How do you optimize iteratively?

- **Objective Function**: the function we want to minimize or maximize
- **Parameters**: what are the parameters of the model that we can change?
- **Update Formula**: what update “step”can we take for these parameters to optimize the objective function?

$$L(\mathbf{w}) = \prod_i g(\mathbf{w}^T\mathbf{x}^{(i)})_{y^{(i)}=1} \cdot (1 - g(\mathbf{w}^T\mathbf{x}^{(i)}))_{y^{(i)}=0}$$

Logistic Regression Optimization Procedure

$$L(\mathbf{w}) = \prod_i g(\mathbf{w}^T\mathbf{x}^{(i)})_{y^{(i)}=1} \cdot (1 - g(\mathbf{w}^T\mathbf{x}^{(i)}))_{y^{(i)}=0}$$

- Simplify $L(\mathbf{w})$ with **logarithm**, $l(\mathbf{w})$

$$l(\mathbf{w}) = \sum_i y^{(i)} \ln\left(g(\mathbf{w}^T\mathbf{x}^{(i)})\right) + (1 - y^{(i)}) \ln\left(1 - g(\mathbf{w}^T\mathbf{x}^{(i)})\right)$$

- **Take** Gradient

$$\frac{\partial}{\partial w_j} l(\mathbf{w}) = -\sum_i \left(y^{(i)} - g(\mathbf{w}^T\mathbf{x}^{(i)})\right) x_j^{(i)}$$

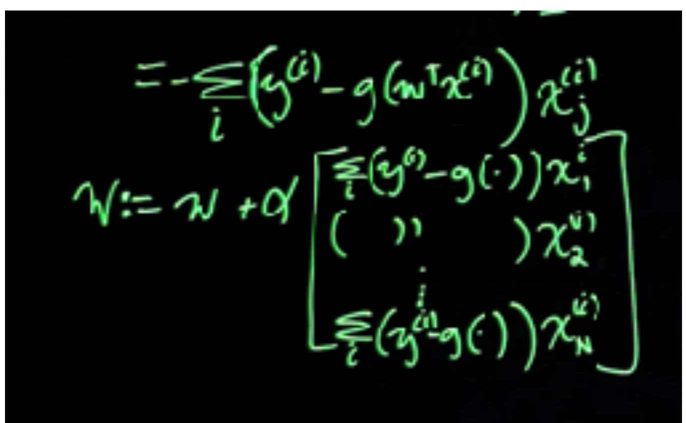
- **Use** gradient to **update** equation for $\mathbf{w}$
  - Video Supplement (also on canvas):
    - https://www.youtube.com/watch?v=FGnoHdjFrJ8

Binary Solution for Update Equation

- Use gradient inside update equation for **w**

$$\frac{\partial}{\partial w_j} l(\mathbf{w}) = -\sum_i \left(y^{(i)} - g(\mathbf{w}^T\mathbf{x}^{(i)})\right) x_j^{(i)}$$

$$\underbrace{w_j}_{\text{new value}} \leftarrow \underbrace{w_j}_{\text{old value}} + \eta \underbrace{\sum_{i=1}^{M} (y^{(i)} - g(\mathbf{w}^T\mathbf{x}^{(i)}))x_j^{(i)}}_{\text{gradient}}$$



Demo

`05. Logistic Regression.ipynb`

Programming
Vectorization
Regularization
Multi-class extension

Other Tutorials:

http://blog.yhat.com/posts/logistic-regression-python-rodeo.html

http://scikit-learn.org/stable/auto_examples/linear_model/plot_iris_logistic.html

For Next Lecture

- **Next time**: More gradient based optimization techniques for logistic regression