Maximum Entropy Classifier

Supervised Machine Learning

CSE538 - Spring 2024

Text Classification

The Buccaneers win it!

President Biden vetoed bill

Twitter to be acquired by Apple

She <u>will</u> drive to the office, to make sure the lawyer gives the <u>will</u> to the family.

<u>*will.n*</u> or <u>*will.v*</u> ?

noun or verb

I like the the movie.

The movie is like terrible.

Supervised Classification

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X - features of N observations (i.e. words)

Y - class of each of N observations

GOAL: Produce a *model* that outputs the most likely class y_i, given features x_i.

$$f(X) = Y$$

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$$
\begin{array}{ccc}
i & X & Y \\
\begin{array}{c} 0 \\ 1 \\ 2 \\ 3 \\ 4 \end{array} &
\begin{pmatrix} 0.0 \\ 0.5 \\ 1.0 \\ 0.25 \\ 0.75 \end{pmatrix} &
\begin{pmatrix} 0 \\ 0 \\ 1 \\ 0 \\ 1 \end{pmatrix}
\end{array}
$$

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Some function or rules to go from X to Y, as close as possible.

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1	0.5	0
2	1.0	1
3	0.25	0
4	0.75	1

Supervised Classification

Supervised Machine Learning: Build a model with examples of outcomes (i.e. Y) that one is trying to predict. (The alternative, *unsupervised* machine learning, tries to learn with only an X).

Classification: The outcome (Y) is a discrete class.

for example: $y \in$ {not-noun, noun}

$y \in$ {noun, verb, adjective, adverb}

$y \in$ {positive_sentiment, negative_sentiment}).

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Binary classification goal: Build a model that can estimate $P(A=1|B=?)$

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Example: Y: 1 if target is verb, 0 otherwise;
X: 1 if "was" occurs before target; 0 otherwise

I was <u>reading</u> for NLP. *We were <u>fine</u>.* *I am <u>good</u>.*

The cat was <u>very</u> happy. *We enjoyed the <u>reading</u> material.* *I was <u>good</u>.*

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Classification as Producing a Probability

Example: Y: 1 if target is a part of a proper noun, 0 otherwise;
X: number of capital letters in target and surrounding words.

They attend Stony Brook University. *Next to the brook Gandalf lay thinking.*

The trail was very stony. *Her degree is from SUNY Stony Brook.*

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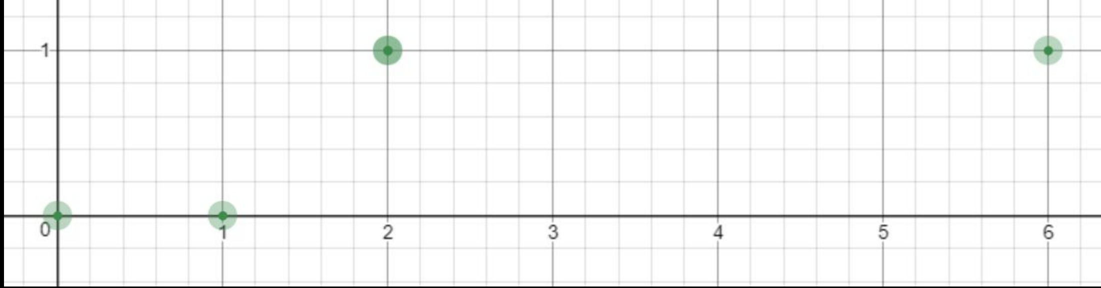
x	y
2	1
1	0
0	0
6	1
2	1

Logistic Regression



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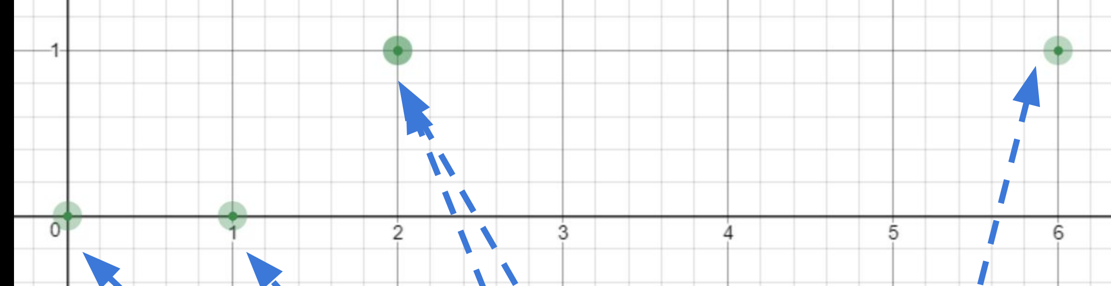

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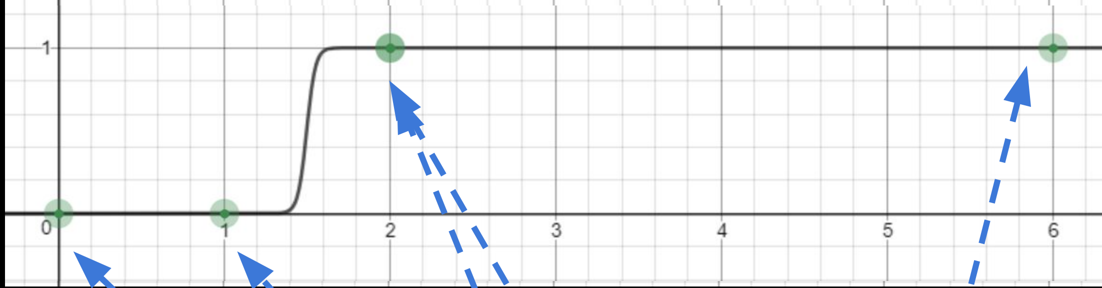

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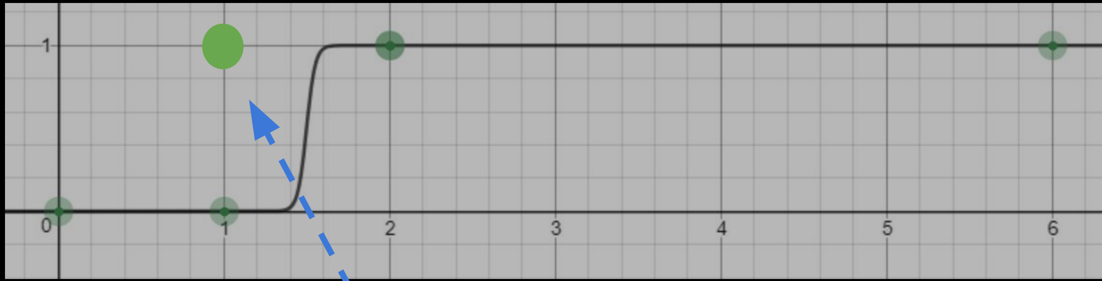

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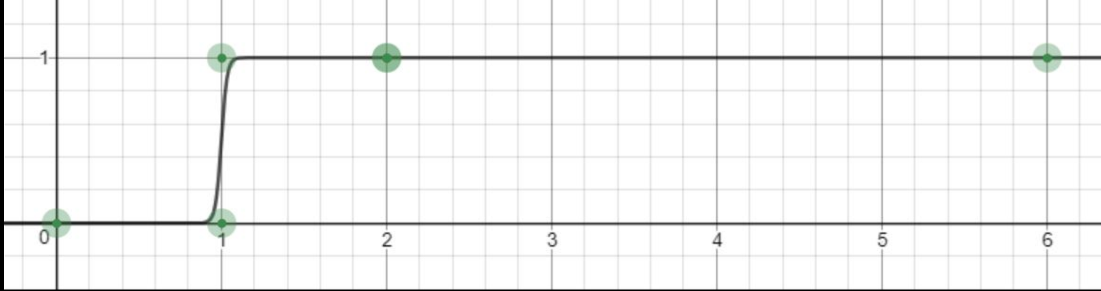

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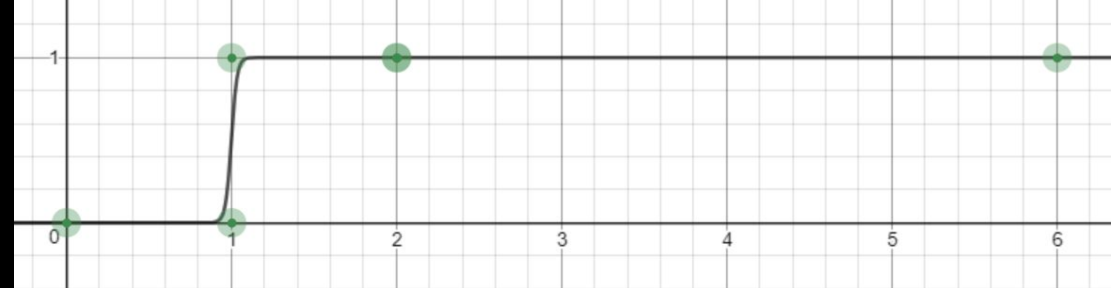

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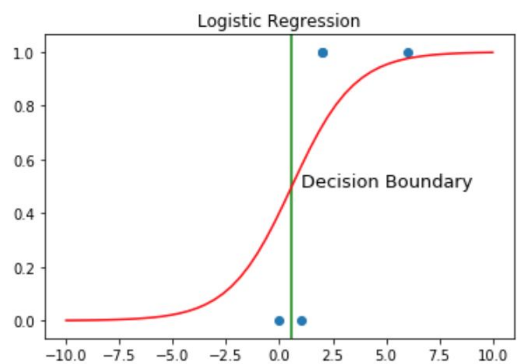

In [78]:
```
-b_0/b_1
```
Out[78]: 0.5824799517820446

In [28]:
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logisticRegr.predict(x)
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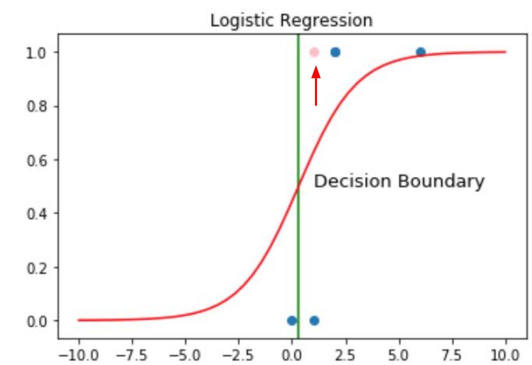
Out[28]: array([1, 1, 0, 1, 1])

Out[80]: [<matplotlib.lines.Line2D at 0x11a60f160>]



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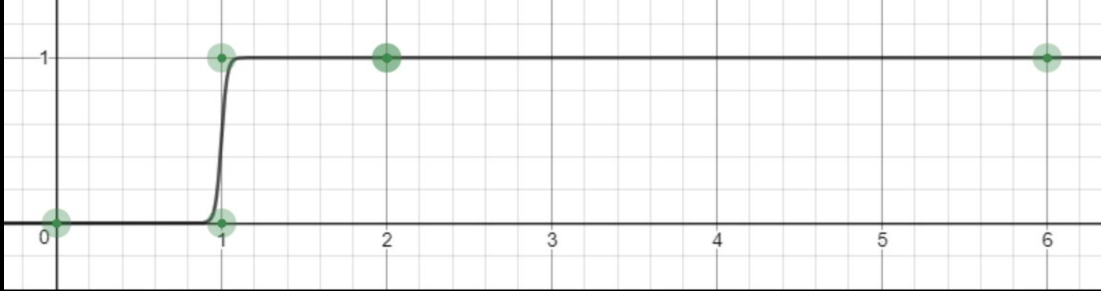

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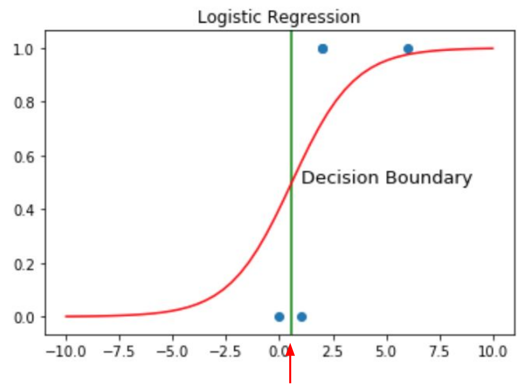


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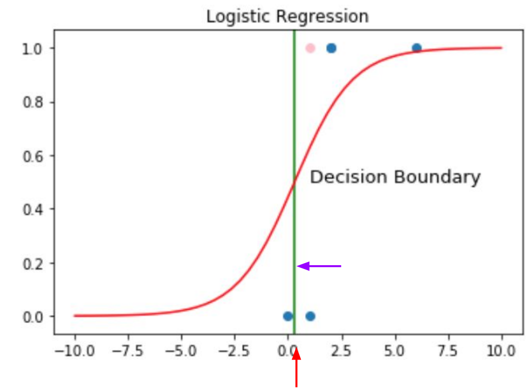


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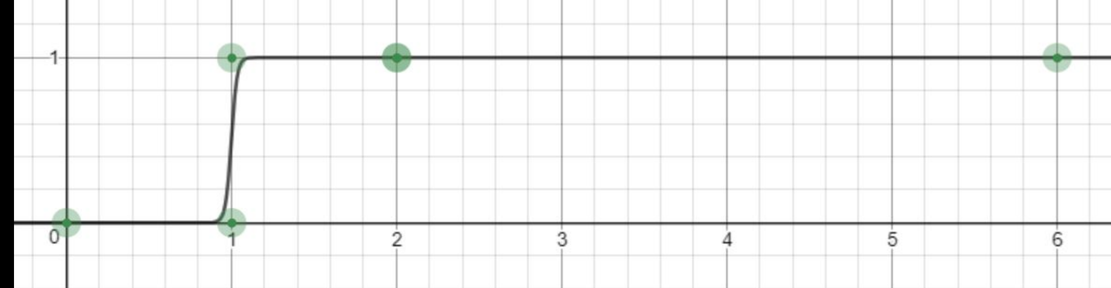

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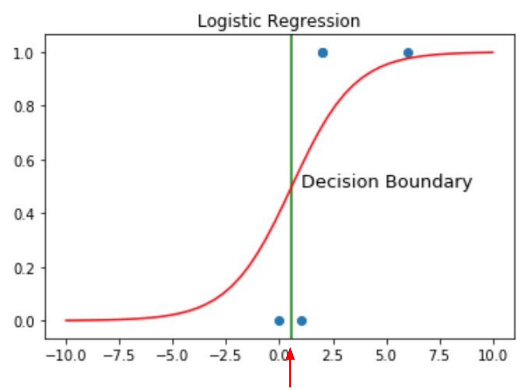


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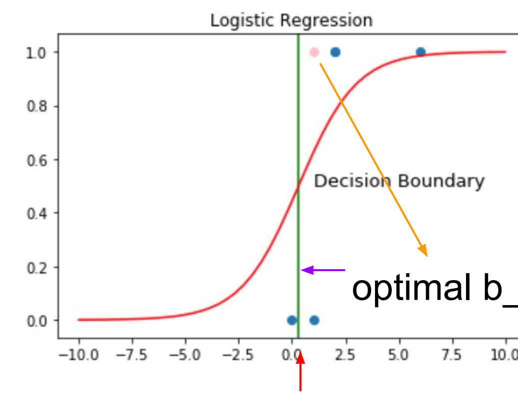

optimal b_0, b_1 changed!

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Logistic Regression on a single feature (*x*)

$Y_i \in \{0, 1\}$; X is a **single value** and can be anything numeric.

$$P(Y_i = 1 | X_i = x) = \frac{e^{\beta_0 + \beta_1 x_i}}{1 + e^{\beta_0 + \beta_1 x_i}}$$

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$$= \frac{1}{1 + e^{-(\beta_0 + \sum_{j=1}^{m} \beta_j x_{ij})}}$$

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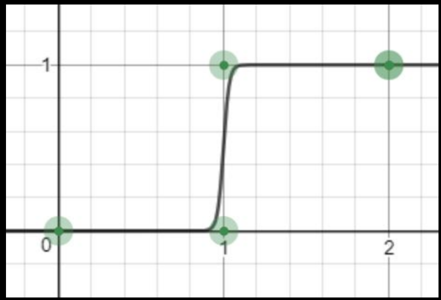
HOW? Essentially, try different B_0 and B_1 values until “best fit” to the training data (example X and Y).



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“best fit” : whatever maximizes the likelihood function:

$$L(\beta_0, \beta_1 | X, Y) = \prod_{i=1}^{n} p(x_i)^{y_i} (1 - p(x_i))^{1-y_i}$$

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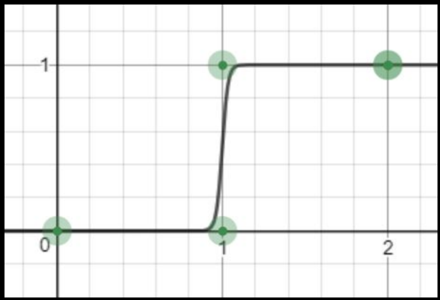

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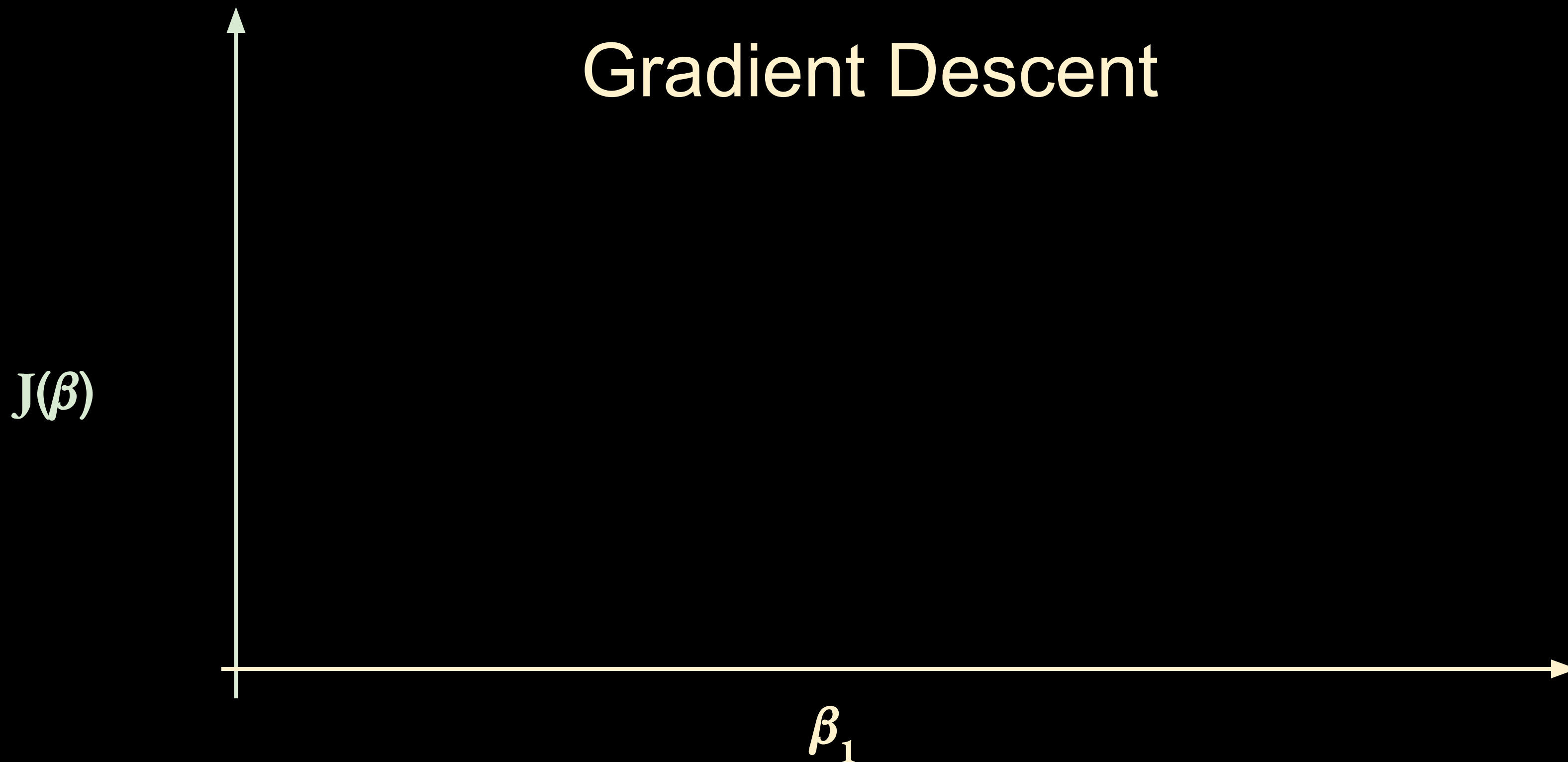
$$\boxed{J(\beta) = -\frac{1}{N} \sum_{i=1}^{N} y_i log\, p(x_i) + (1 - y_i) log\, (1 - p)(x_i))}$$

Gradient Descent



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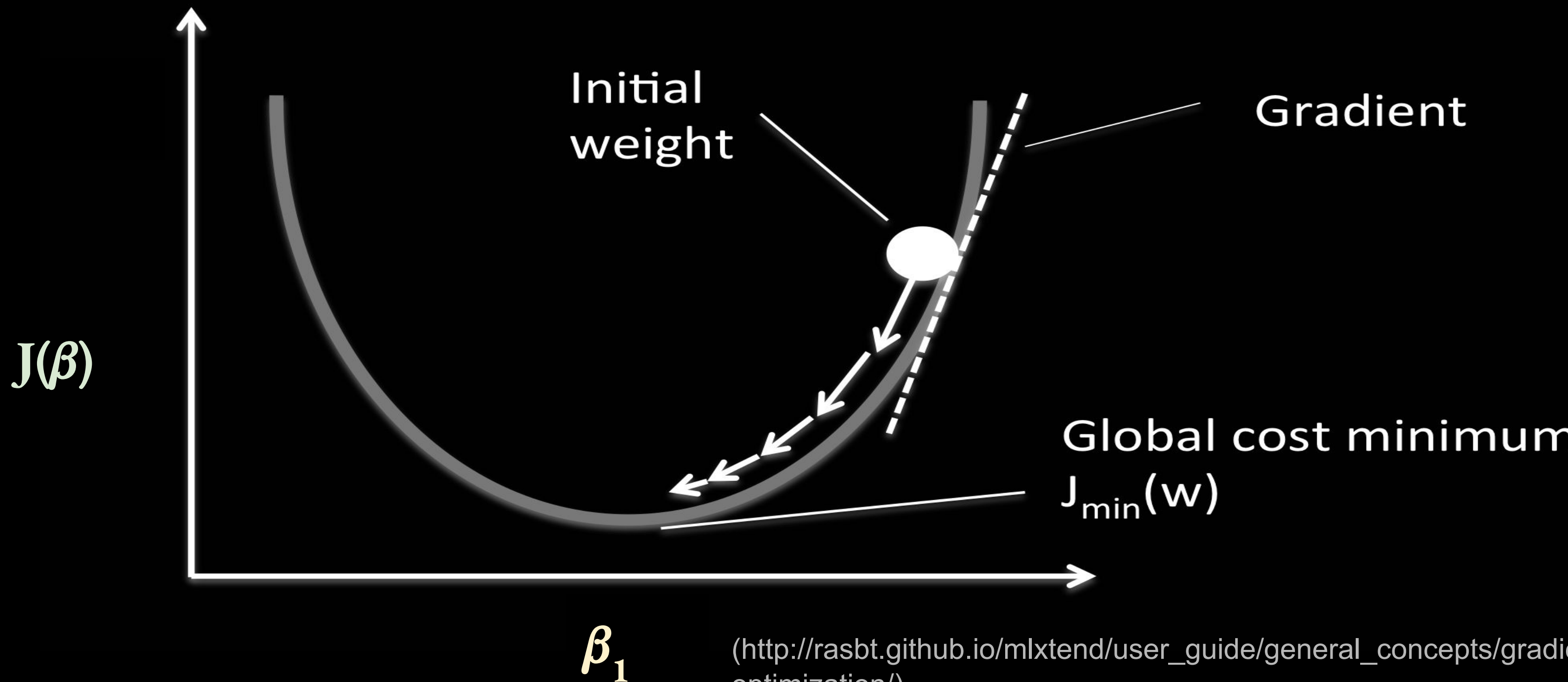

(http://rasbt.github.io/mlxtend/user_guide/general_concepts/gradient-optimization/)

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