Supervised Learning

Regression and Classification

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Regression

- The regression problem asks to predict a numerical variable's value given the values of other variables.
- Easiest example is with two variables x and y:
  - x is the variable in input
  - y is the variable we want to predict

x	y
1	3
2	5
3	7
4	9
5	11

Training data: x is the input data, y is the label data.

Learning

Learning task: **what's the mapping from x to y?**

Testing

Try to "learn" from the training data an hypothesis function **h**.

What is h(6)? That is, what's y when x is 6?

x	y
6	?

Regression example 1/2

- We have the data from 10 thousand houses in the U.S.

m=10000

City	Rooms	SQM	Price
Los Angeles	3	130	420000
Los Angeles	2	60	380000
...	...	...	...
Albuquerque	2	140	220000
Albuquerque	3	150	250000

- **Goal:** learn a function (model) that can infer the Price given all the other variables, for houses not in the 10 thousand dataset:

X

City	Rooms	SQM
Los Angeles	5	230

y

Price
?

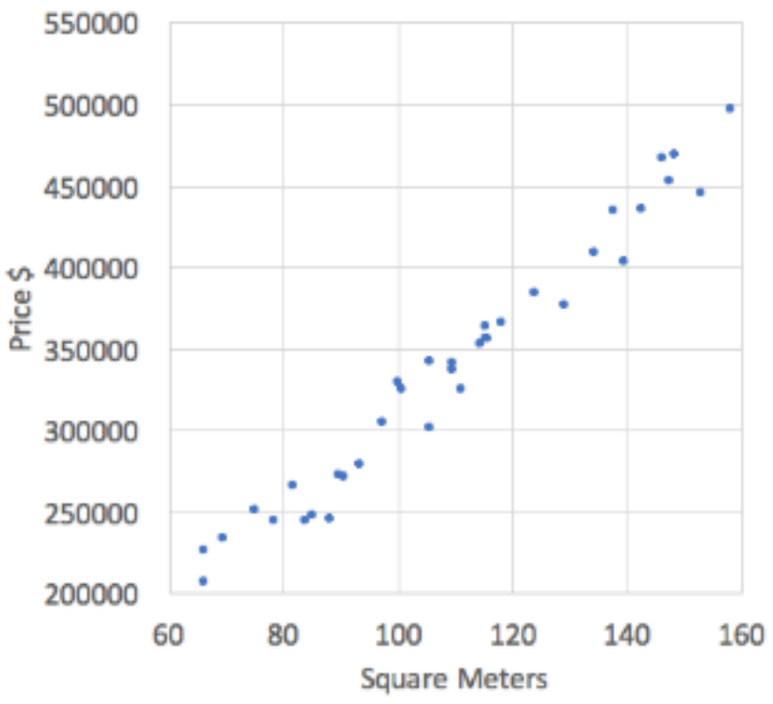
Regression example 2/2

- The houses' prices example is an example of **regression** task:
  - Among the variables there is the output variable (Price)
  - The output variable is the ground truth, because it's the actual price of the house
  - The output variable we want to predict is a numerical value

City	Rooms	SQM
Los Angeles	5	230

Price
?

- To visualize things better we will have examples with only two variables (one used as input one as output)
- All the process can be generalized for n variables.



Linear regression

- We define regression as the general task of predicting the real value of a variable using the other variables as input.
- The model we want to learn is a function *f* from *n* real values x_i to one real value *y*:

$$y=f(x_1,\ldots,x_n)$$

- The learned model is called *hypothesis* function *h*:

$$y=h(x_1,\ldots,x_n)$$

- When ***h* is a linear function** on the input variables x_i, the regression task is called **linear regression**.

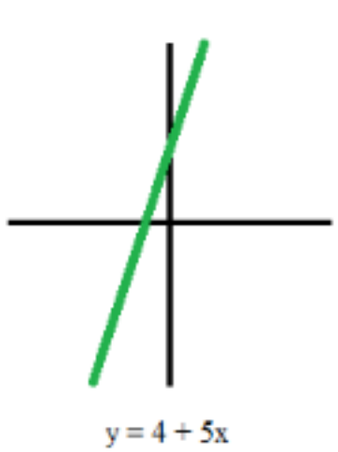
Linear function

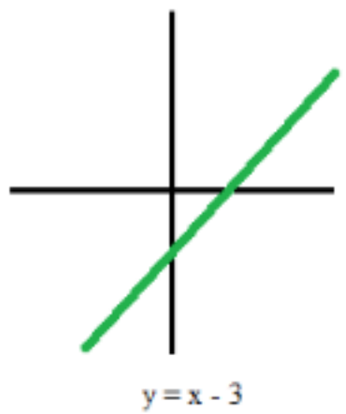
- A linear function is a function of this form:

$$y = f(x_1,...,x_n) = w_1x_1+...+w_nx_n+b$$

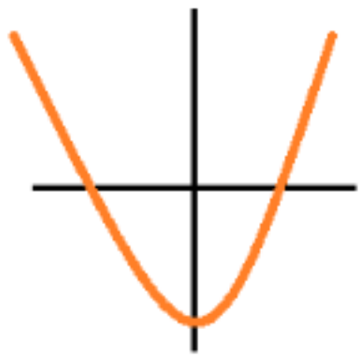
- When n=1 (only one input variable), the plotted function has the **shape of a straight line**. When n=2 it takes the shape of a straight plane etc.
- Straight lines and straight planes are examples of linear functions.

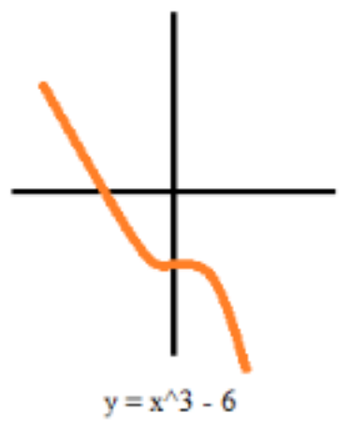
Linear functions





Non-linear functions





Linear regression: parameters

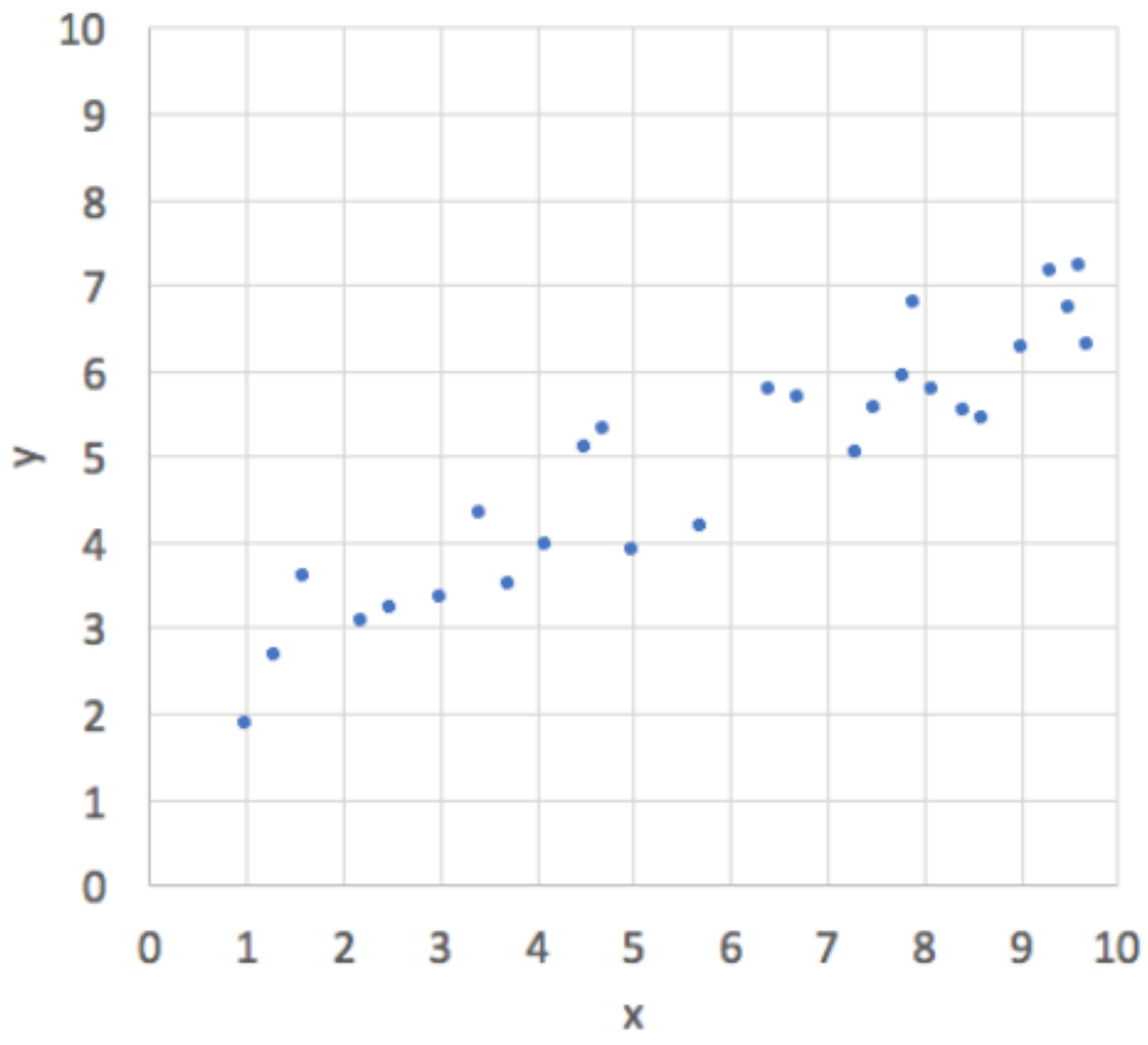
- Recall, a linear function is a function of this form:

$$y = f(x_1,...,x_n) = w_1x_1+...+w_nx_n+b$$

- This means that the function that models our data is already defined!
- What's missing? **What are the parameters we need to "learn"?**
  - The x_i variables are the ones **given in input**, so we already have them. (E.g. the square meters of the house)
  - The **w_i coefficients are not known!**
    - In a straight line, the coefficient is the **slope** of the linear function!
    - In ML they are also called **weights**: assuming that you have scaled your variables (e.g. between 0 and 1) they tell you **how much a variable contributes** to the final result (the *y*)
  - The **b** parameter is **also not known**!
    - In a straight line, this is the **y-intercept** of the line: the point where the line intercept the y axis.
    - In ML this is also called **bias term** or **bias weight**.

Example: data points

- Let's clarify these new notions with an example.
- We have plotted some data points, each point is an observation with two variables: x and y.



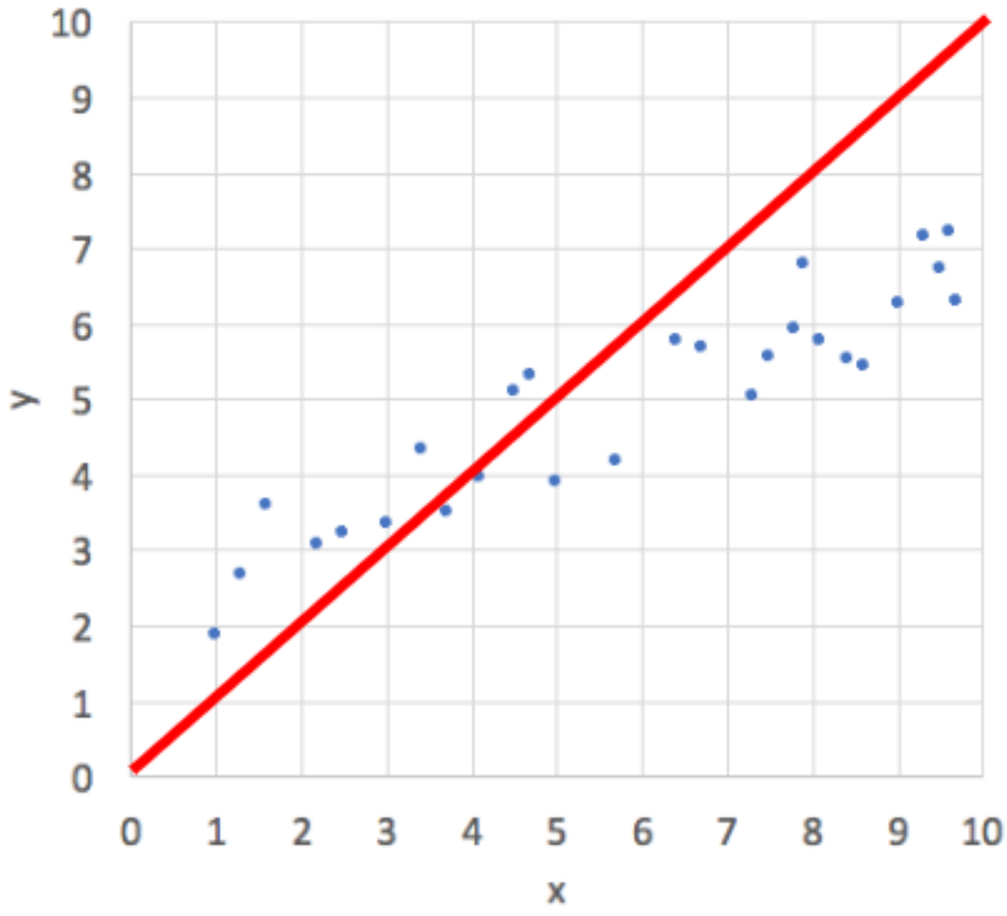
Example: slope 1/3

- Let's simulate a learning process: we need to learn the slope on the line.
- To keep things simple, we focus on the angle only, setting the y-intercept to 0.

1. **Let's try with a slope w = 1**: this means the line will have a 45° slope.
2. Having a y-intercept (b parameters) set to 0, the hypothesis function is:

$$y = h(x) = wx = x$$

3. By plotting the line on the figure we can visually evaluate how much this hypothesis match the actual data.



- Is this hypothesis good enough?
- We will see later how to **measure precisely the distance between the actual data and the hypothesis**.
- But for sure can do better!

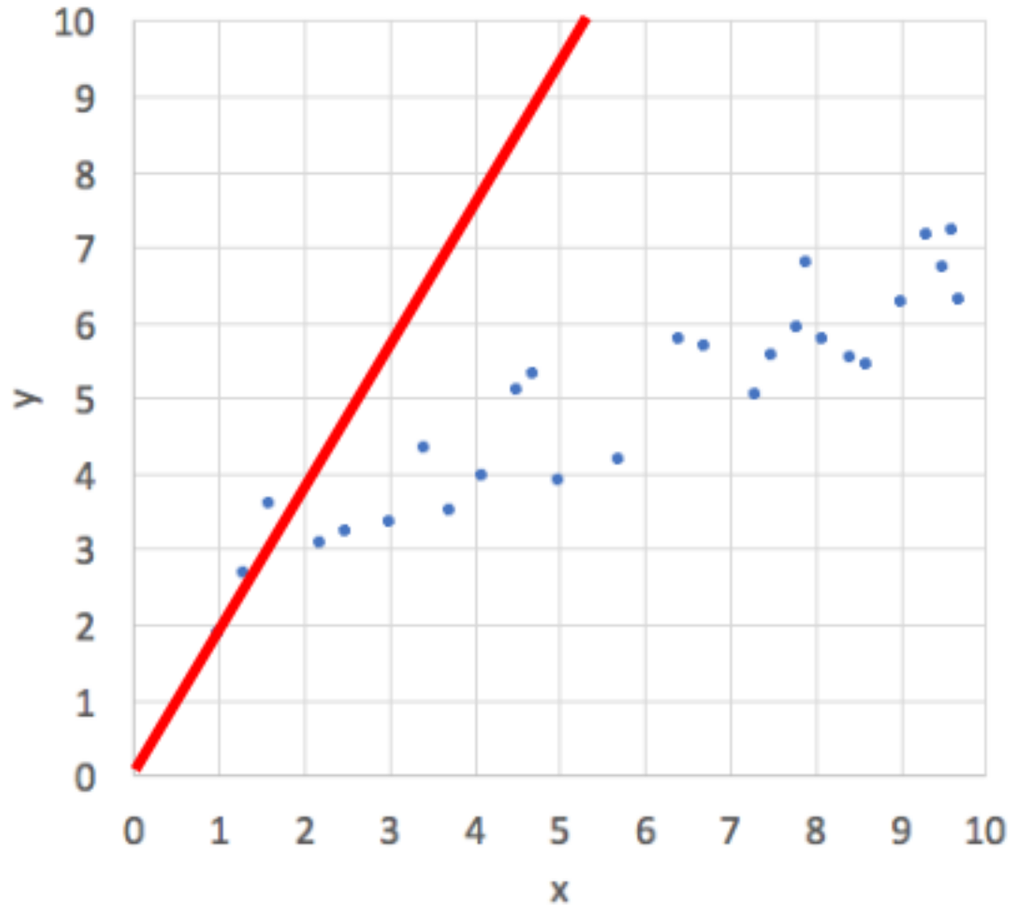
Example: slope 2/3

- Let's simulate a learning process: we need to learn the slope on the line.
- To keep things simple, we focus on the angle only, setting the y-intercept to 0.

1. **Now let's try with a slope w = 2**!
2. Having a y-intercept (b parameters) set to 0, the hypothesis function is:

$$y = h(x) = 2x$$

3. By plotting the line on the figure we can visually evaluate how much this hypothesis match the actual data.



- Is this hypothesis better?
- The hypothesis **seems worse than before**.

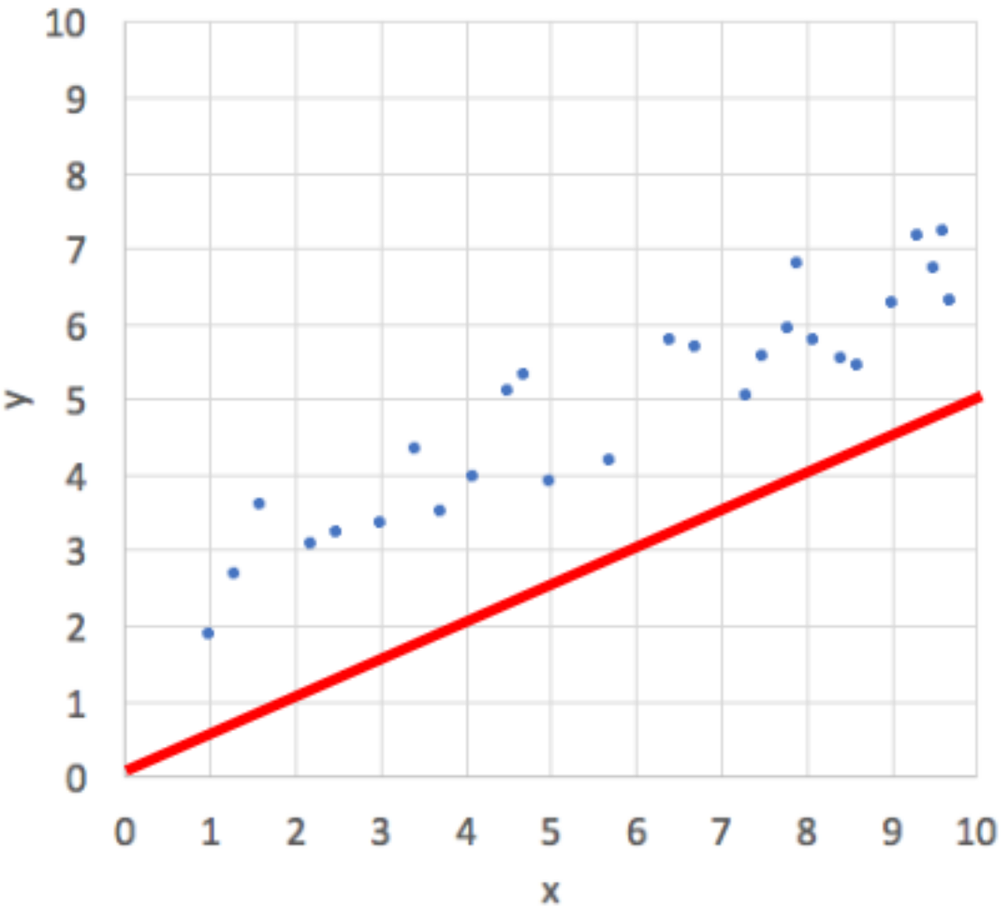
Example: slope 3/3

- Let's simulate a learning process: we need to learn the slope on the line.
- To keep things simple, we focus on the angle only, setting the y-intercept to 0.

1. **Now let's try with a slope w = 0.5!**
2. Having a y-intercept (b parameters) set to 0, the hypothesis function is:

$$y = h(x) = \frac{1}{2} x$$

3. By plotting the line on the figure we can visually evaluate how much this hypothesis match the actual data.



- Is this hypothesis better?
- The hypothesis seems **quite accurate, at least for the slope**.
- We should now learn **what's the best value for the bias term *b***.

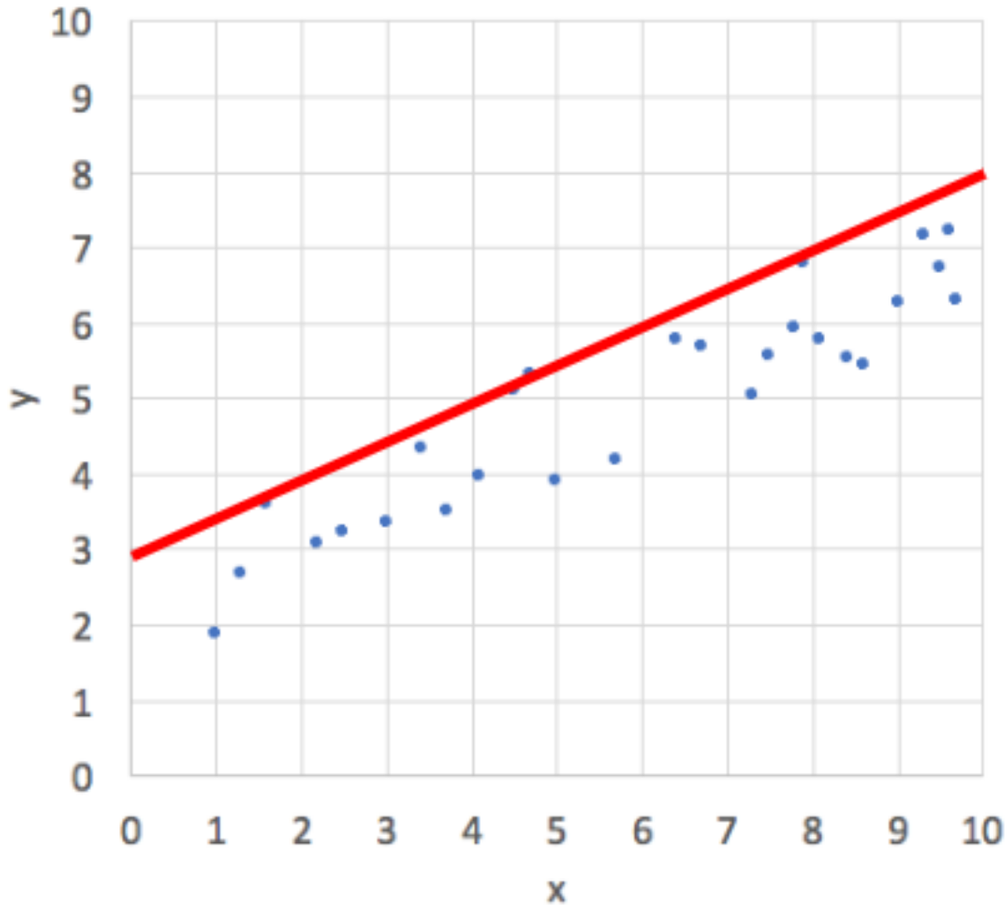
Example: bias term 1/2

- We have now a **good slope but a clearly wrong bias term** (the y intercept parameter)
- Let's try again some reasonable value

1. **Now let's try with a bias b = 3!**
2. Having already set the weight to 0.5, the hypothesis function is:

$$y = h(x) = \tfrac{1}{2} x + 3$$

3. By plotting the line on the figure we can visually evaluate how much this hypothesis match the actual data.



- Are the points approximately around the line?
- **It seems slightly above. We should try a lower value for *b*.**

Example: bias term 2/2

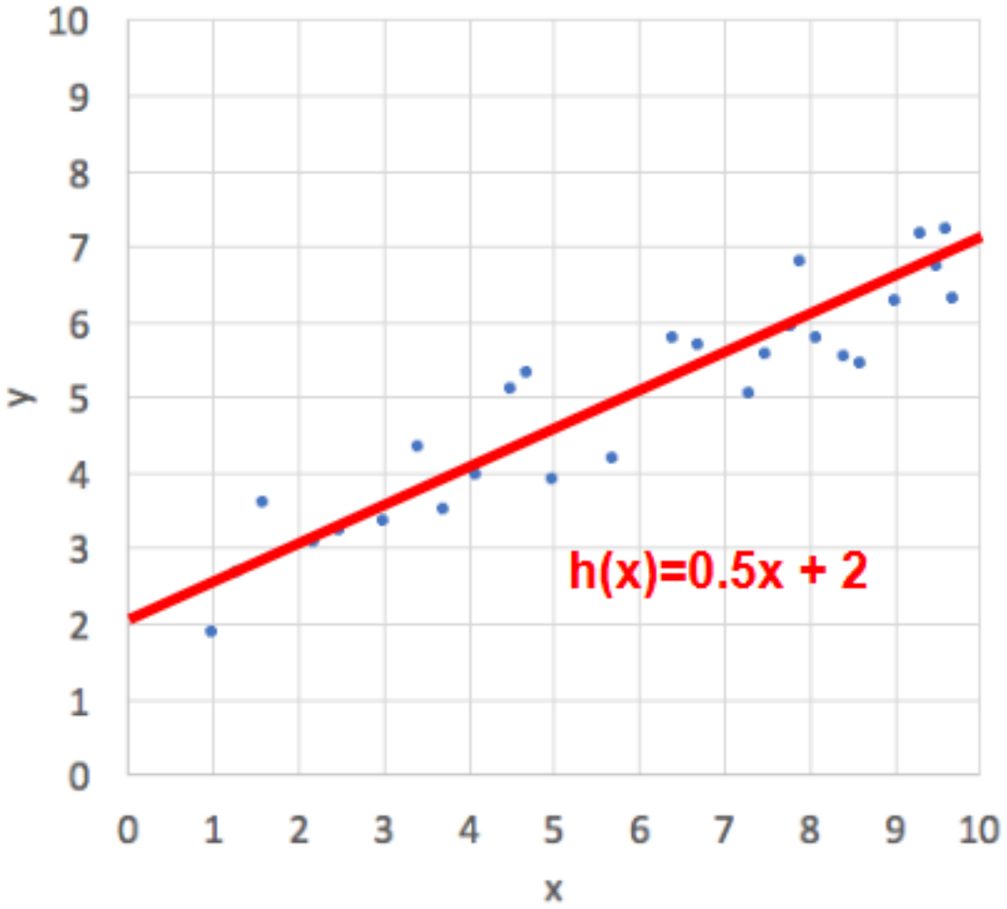
- We have now a good slope but a clearly wrong bias term (the y intercept parameter)
- Let's try again some reasonable value

1. **Now let's try with a bias b = 2**!
2. Having already set the weight to 0.5, the hypothesis function is:

$$y = h(x) = \tfrac{1}{2} x + 2$$

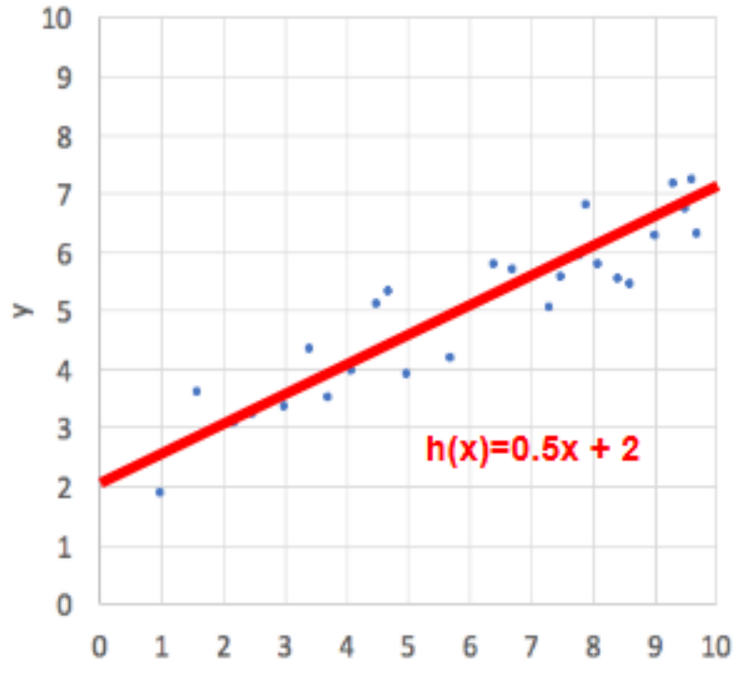
3. By plotting the line on the figure we can visually evaluate how much this hypothesis match the actual data.

- **This hypothesis looks quite right!**



Example: observations

- The machine learning algorithm we have simulated is rather naive:
  - It has no precise way to measure how close we are to the optimal hypothesis.
  - It makes almost random guesses to generate new hypothesis.
- This means that a good machine learning model should have:
  - A way to measure how good (or how bad) an hypothesis is.
  - A smart algorithm that tunes the weights until the measure of badness is very low (or conversely the measure of goodness is very high).



Loss function

- In ML, the measure used to evaluate the hypothesis is called a **loss function**.
- Intuitively, a **loss** function measures how **bad** the model is with respect to the actual data.
- The most common it's the mean squared error: it's the average squared distance between the training data and the hypothesis.
  - Mean because we want to consider all the *m* data points in the training set, so we average all the distances
  - Squared to enforce the distance to be non-negative.

$$\frac{1}{m}\sum_{i=1}^{m}(h(x_i) - y_i)^2$$

Arithmetic mean

Difference between the y predicted using the hypothesis function and the actual y

We square the difference to enforce non-negativity

Optimization

- Now that we have a **tool to measure the error of an hypothesis function**, we want the error to be the smallest possible.
- This means the our ***objective function*** is to find the variables values (weights and bias) that ***minimize*** the error.

$$minimize: \frac{1}{m}\sum_{i=1}^{m}(h(x_i) - y_i)^2$$

- Using the *argmin* notation and replacing h(x) with the linear function:

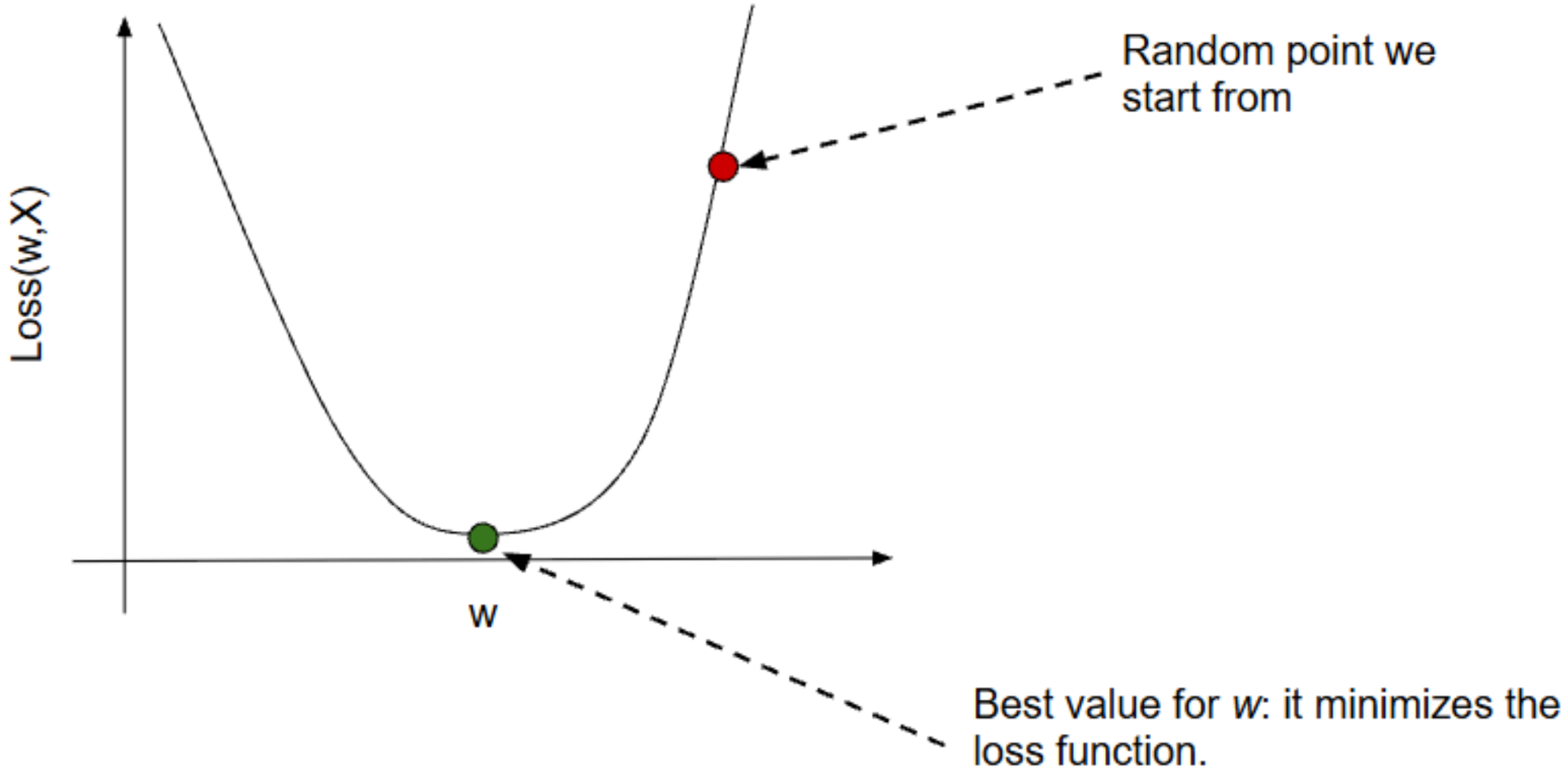
$$\underset{w,b}{\operatorname{argmin}} \frac{1}{m}\sum_{i=1}^{m}((wx_i + b) - y_i)^2$$

Optimization algorithms

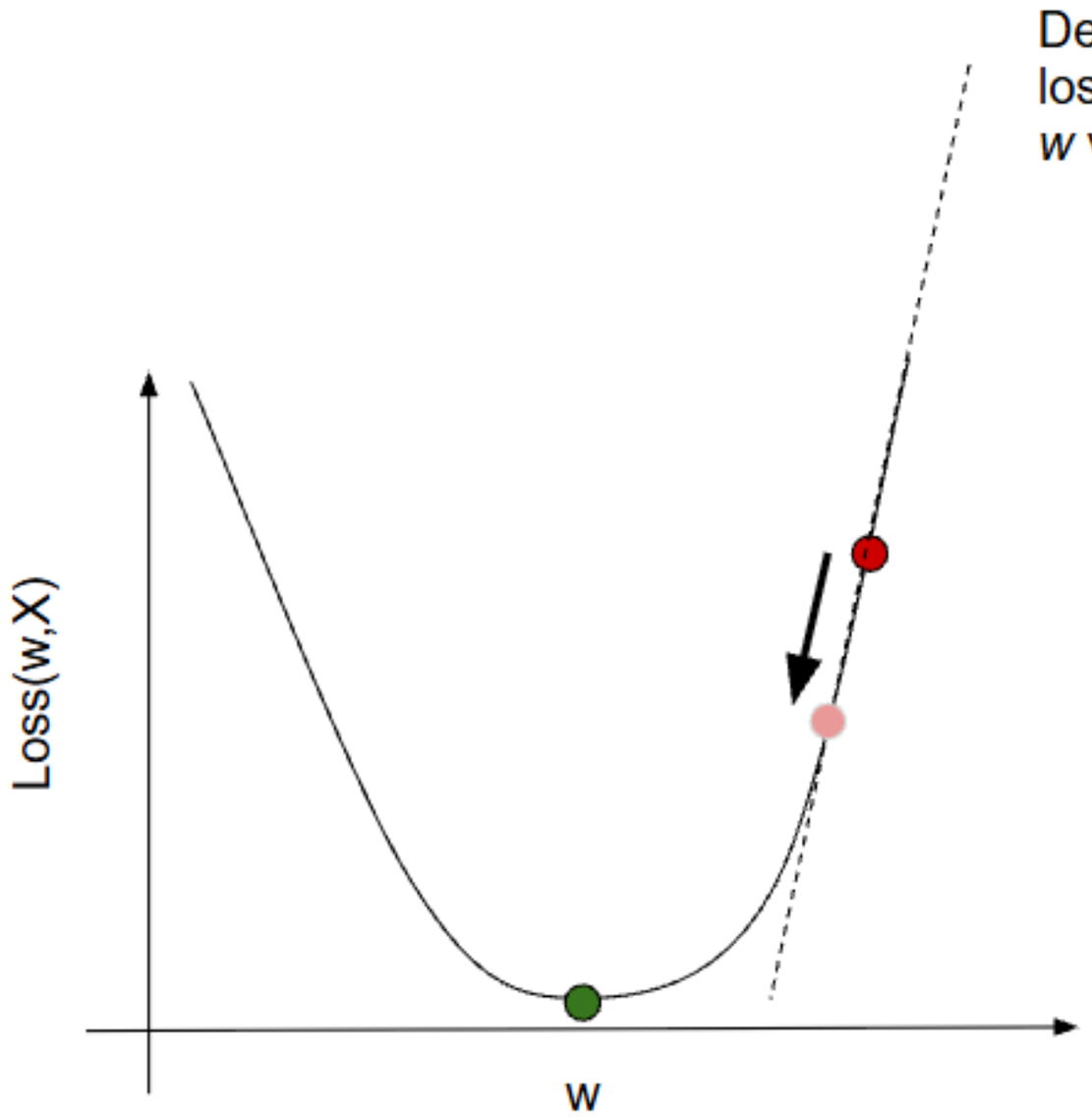
- Most popular and effective optimization algorithm in ML is **gradient descent**:
- It **iterates** through 4 steps until the **loss is smaller than a tolerance value**:
  1. Compute the gradient (that is the derivative or slope) of the loss function.
  2. The **sign of the gradient** tells us if the loss increase (positive) or decrease (negative) moving to the right.
     Recall that we want to reach the minimum:
     a. If it increase, we should move the weight to the left (subtract a small value)
     b. If it decrease, we should move to the weight right (add a small value)
  3. Update the hypothesis with the new weights
  4. Compute again the loss.

Gradient descent example 1/6

- For simplicity, we consider only one parameter *w* to be learned
- The loss function with respect to *w* it's a convex function, thus it has a global minimum.



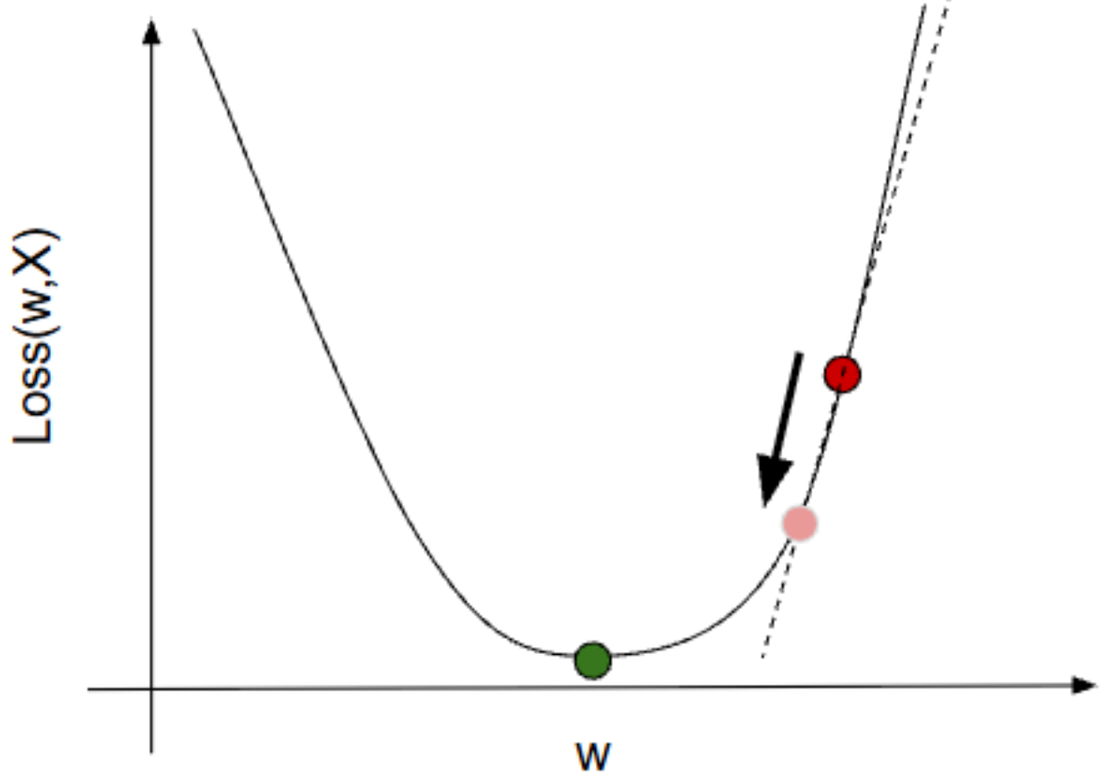
Gradient descent example 2/6



- The gradient is positive (increasing)
- In order to move toward the minimum, we should subtract a small value from *w*.

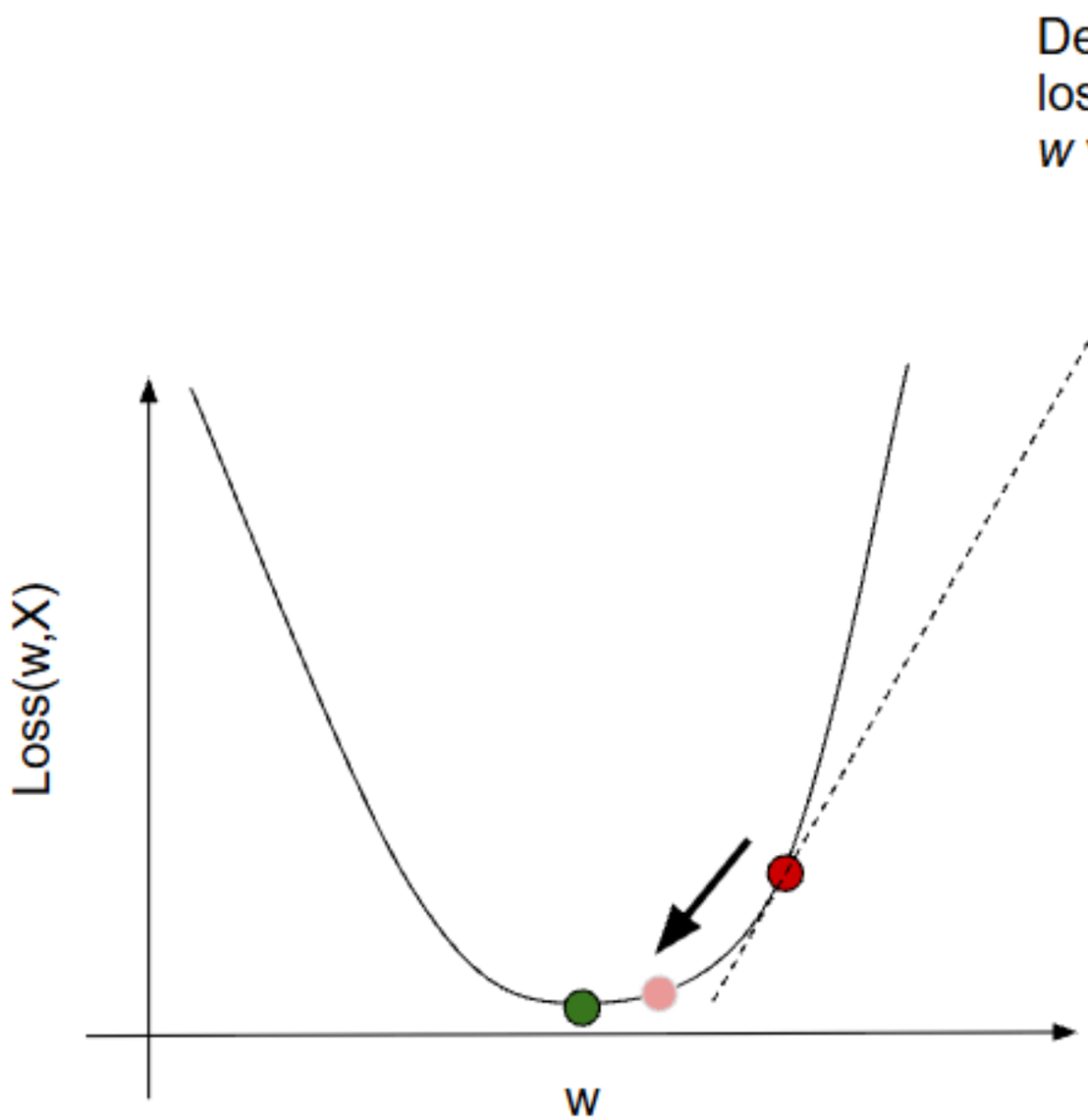
Gradient descent example 3/6

Derivate (gradient) of the loss function for the current *w* value



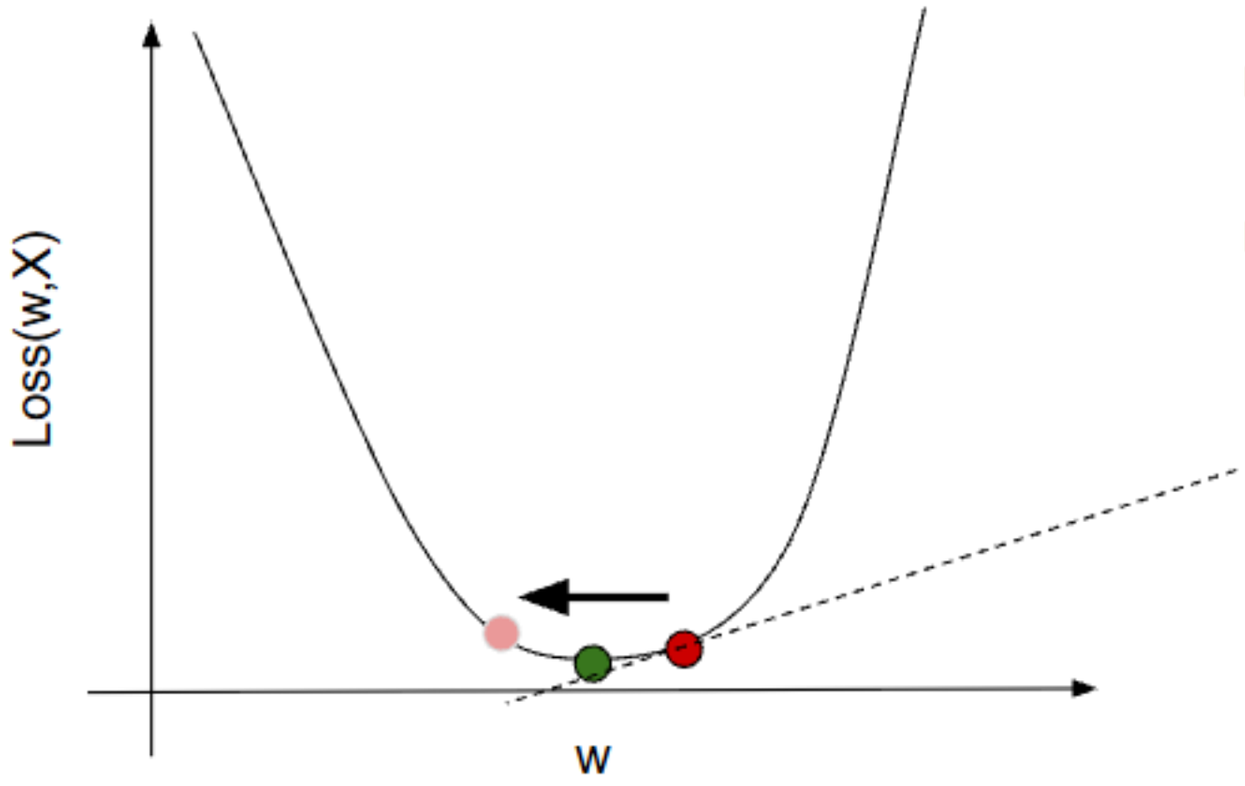
- The gradient is still positive (increasing)
- In order to move toward the minimum, we should subtract a small value from *w*.

Gradient descent example 4/6



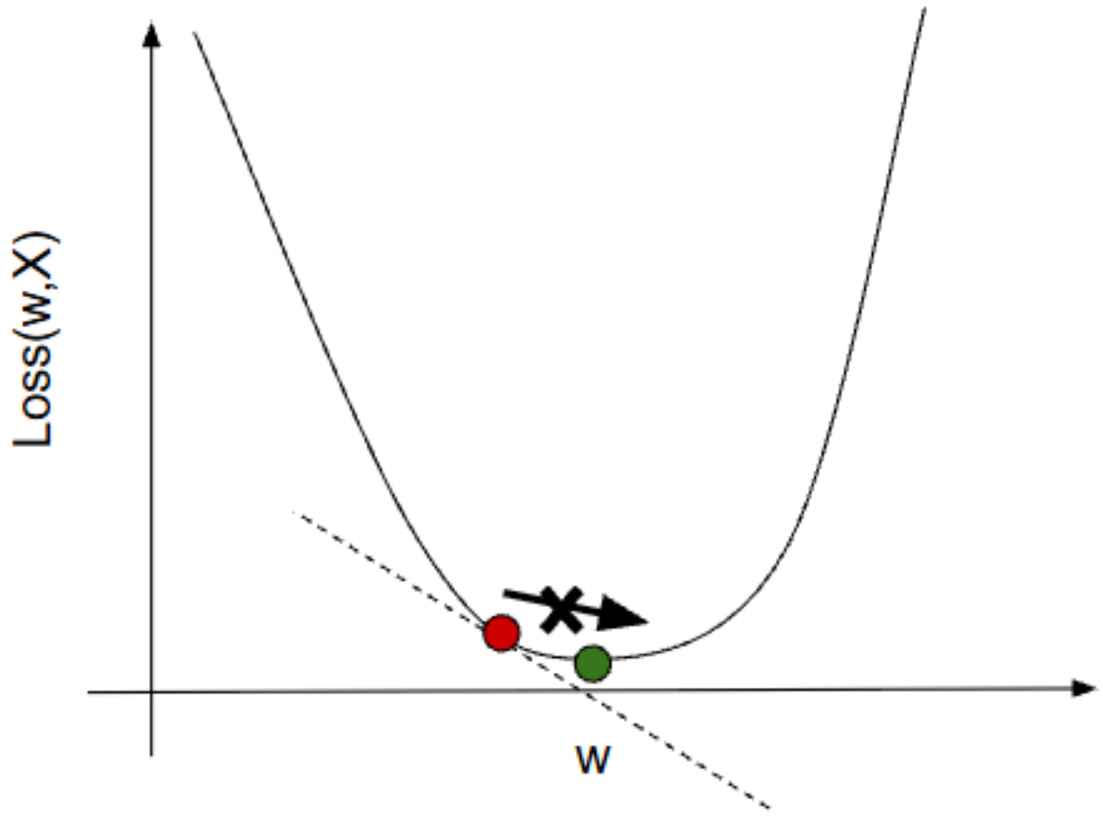
- The gradient is still positive (increasing)
- In order to move toward the minimum, we should subtract a small value from *w*.

Gradient descent example 5/6



- The gradient is still positive (increasing)
- In order to move toward the minimum, we should subtract a small value from *w*.

Gradient descent example 6/6



- The gradient **now is negative** (decreasing)
- In order to move toward the minimum, we should **add a small value to *w*.**
- However, we could decide that the loss is **small enough** and **stop our descent iterations.**

Testing set

- **Important:** the loss function is made to evaluate the hypothesis **on the training set**! It measures the distance between the training data and the hypothesis.
- If the loss is 0, it means that the hypothesis is **perfectly fitting** the training data.
- Yet, this hypothesis could be inaccurate **with unseen data**: data that is not in the training set.
  - This phenomenon is called ***overfitting***: the model is extremely good (overfitted) on the training data but unable to generalize on new data.

- In order to actually test our model we must use a set of data that the learning algorithm has never seen: a ***testing set.***

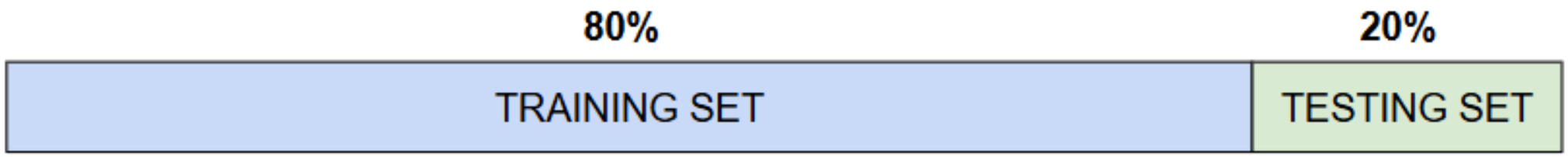
Train/test split

- Usually in a data mining process the data **is not already** splitted into training and testing set.
- In splitting between training and testing set you should consider the following:
  - The more data you have in the training the better will perform the learned model.
  - The more data you have in the testing the better will be the estimation of accuracy (e.g. if you guess just one example you will have 100% accuracy, but it's not a significant estimation)

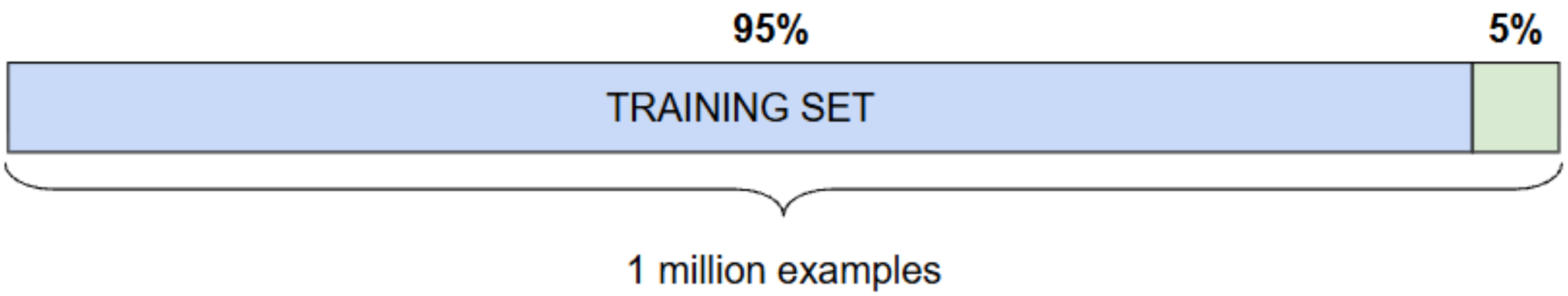
- IMPORTANT: both training and testing set **must come from the same distribution**. For example:
  - You can't train on the houses' prices in L.A. and test on the houses in N.Y.
  - You can't train on pictures taken with the smartphone and test it on pictures taken from Google Images.

Train/test split ratio

- The rule-of-thumb is to split **80/20** following the Pareto principle: 80 for training and 20 for testing.



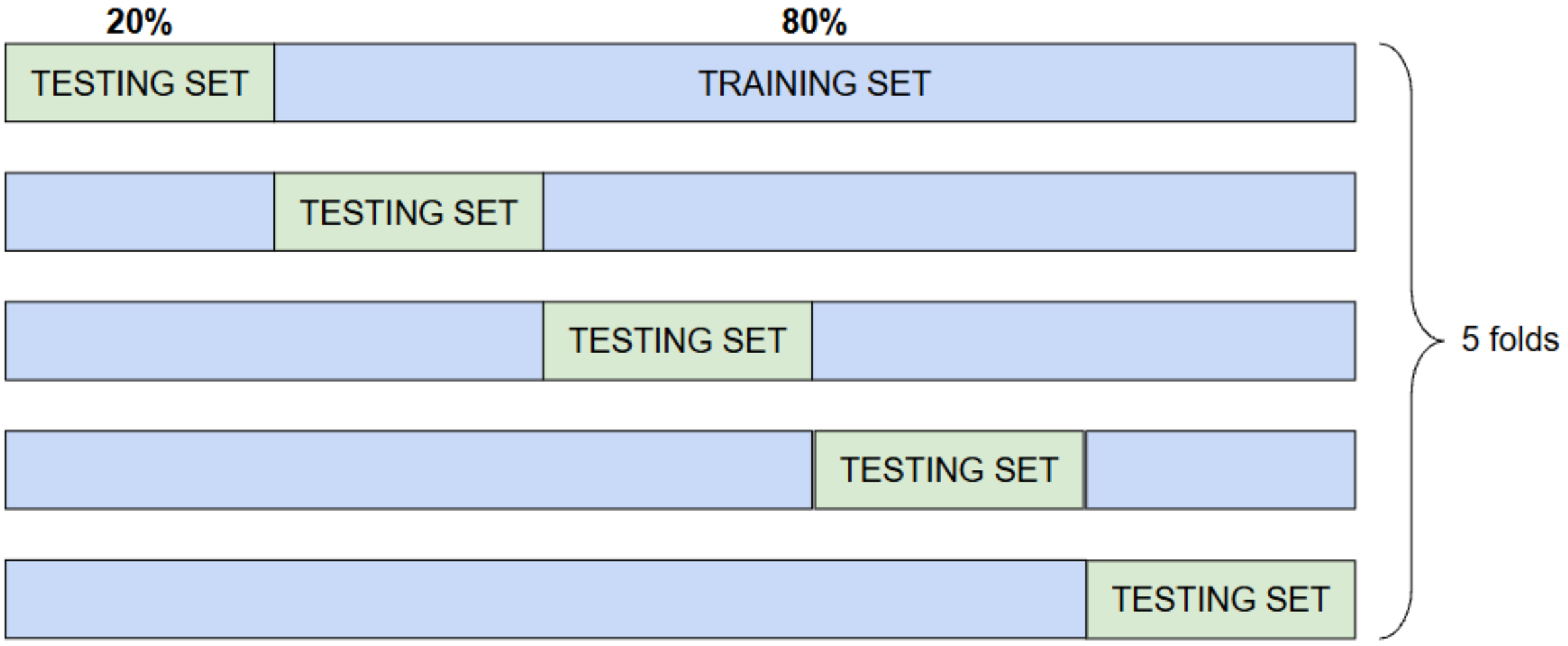
- However if you have many examples, you may decrease the size of testing set to have a more accurate model with a still significant testing set.



- What if we want to use **all the data** both for training **and** testing?

Cross-Validation (CV)

- The idea of cross-validation is to rotate over testing/training set split, so that each example will be used for training and for testing.
- The fraction of the testing set will determine the number of rotations, also called “folds”. For example, using a testing set of 20%, that is ⅕ , we will have a 5-folds cross validation:



Cross-Validation: limit scenarios

- A **2-fold** cross-validation splits the data 50/50:
  - 1st fold: the first half is used for testing, the other for training
  - 2nd fold: the first half is used for training, the other for testing
- A **m-fold** cross-validation (m is the number of examples in the whole dataset) splits the data 1/m:
  - 1st fold: first example is used for testing, all the rest (1-m examples) is used for training
  - 2nd fold: second example is used for testing, the first example and all the other examples from the third are used for training
  - …
  - m-th fold: first m-1 examples are used for training, last example is used for testing.

- Note on CV: **the error of the model will be the average of all the errors**. E.g. in the m-fold CV it will be the average of m error values.

HOME PRACTICE

-

BEGIN

Used software: Jupyter, Sci-kit Learn
Find them in the Anaconda package here: https://www.anaconda.com/

Jupyter demo: Diabetes data

- Let's clarify these new notions with an example.
- We are gonna use a dataset of medical data from patients with diabetes.
- There are 10 features variables (input) such as patients info and measurements:
  - Age
  - Sex
  - Body Mass Index (BMI)
  - Blood pressure
  - 6 blood serum measurements
- The target variable (output) is a quantitative **measure of disease progression** one year after the measurements.
- The 10 features have been already **mean centered** (their mean is 0) and **scaled**.
- For our first experiment, we are going to use **only the BMI** as feature variable, so that we can plot the data points and the regression line in 2D.

Plotting in Jupyter

Linear Regression Example

This example uses the only the BMI feature of the `diabetes` dataset, in order to illustrate a two-dimensional plot of this regression technique. The straight line can be seen in the plot, showing how linear regression attempts to draw a straight line that will best minimize the residual sum of squares between the observed responses in the dataset, and the responses predicted by the linear approximation.

The coefficients, the residual sum of squares and the variance score are also calculated.

First of all we always need to put a "magic" directive for Jupyter if we want matplotlib plots to show directly in the notebook (instead of being saved in a file)

In [1]:
```
%matplotlib inline
```

Loading libraries and data

We now load all the need libraries for plots, numerical manipulation, machine learning, and we load the diabetes dataset that is embedded in the sklearn library.

In [2]:
```
import matplotlib.pyplot as plt
import numpy as np
from sklearn import datasets, linear_model
from sklearn.metrics import mean_squared_error, r2_score

# Load the diabetes dataset
diabetes = datasets.load_diabetes()
```

In diabetes.data we have the input matrix X. Let's see the shape of this matrix:

In [3]:
```
diabetes.data.shape
```

Out[3]:
```
(442, 10)
```

So we have a matrix of 442 rows, one for each patient (the number *m* of examples), and 10 columns, one for each feature variable (the number *n* of input variables). What are the actual features names?

Features selection

What are the actual features names?

In [4]:
```
print(diabetes.feature_names)
```

```
['age', 'sex', 'bmi', 'bp', 's1', 's2', 's3', 's4', 's5', 's
6']
```

For our first experiment let's just take the bmi feature, which is a strong predictor for diabetes levels. Starting from the first feature that has index 0, we want the third that has index 2:

In [5]:
```
# Use only one feature
diabetes_X = diabetes.data[:, np.newaxis, 2]
print diabetes_X
```

```
[-0.01482845]
[ 0.00672779]
[-0.06871905]
[-0.00943939]
[ 0.01966154]
```

Train/Test Split

The current matrix has all the patients and only one feature. We now split between training and testing sets using only the last 20 examples for testing and the remaining patients for training:

In [6]:
```
# Split the data into training/testing sets
diabetes_X_train = diabetes_X[:-20]
diabetes_X_test = diabetes_X[-20:]

# Split the targets into training/testing sets
diabetes_y_train = diabetes.target[:-20]
diabetes_y_test = diabetes.target[-20:]
```

We now have two matrices X (with only one column), one for training and one for testing, and two vectors y of target labels, one for training and one for testing. Next step is loading the linear regression model from Scikit Learn.

Training (optimization)

In [7]:
```
# Create linear regression object
regr = linear_model.LinearRegression()
```

This model has now empty weights, we must model the hypothesis through optimization. In Scikit Learn, as well as for all ML libraries for Python, the method for training is called *fit*. In supervised models it usually takes two variables: the X matrix of training input data and the y vector of training output labels:

In [8]:
```
# Train the model using the training sets
regr.fit(diabetes_X_train, diabetes_y_train)
```

Out[8]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=1,
 normalize=False)
```

We now have an hypothesis function! We can call it using the *predict* method on the regression model *regre* we just trained. We may want to predict only one value (e.g. if a patient come to us) or a whole set of examples all at once. In this case we want to predict the diabetes level for all the patients in the testing set to check how the differ from the actual true data:

Testing (prediction)

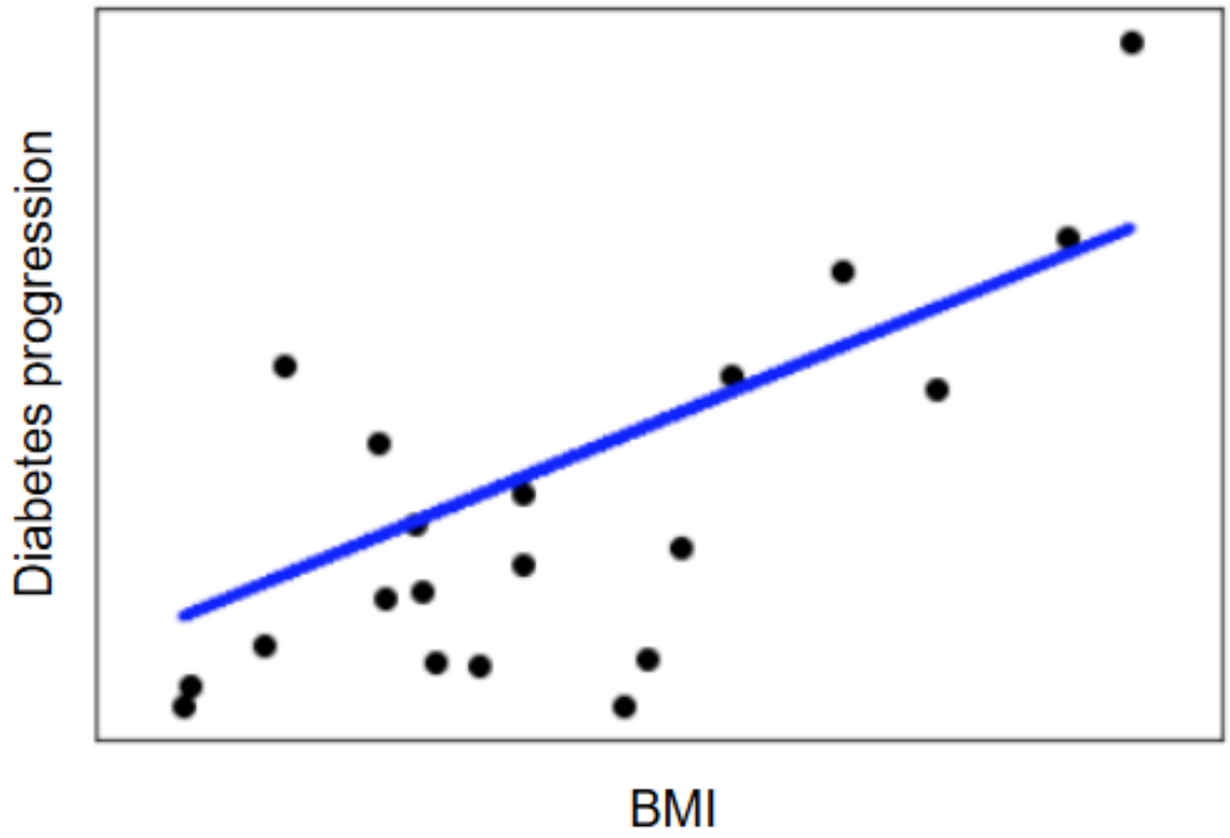
In [9]:
```
# Make predictions using the testing set
diabetes_y_pred = regr.predict(diabetes_X_test)
```

We can finally compare the predicted y with the true y and compute the accuracy as mean square error and variance from the truth:

In [10]:
```
# The mean squared error
print("Mean squared error: %.2f"
      % mean_squared_error(diabetes_y_test, diabetes_y_pred))
# Explained variance score: 1 is perfect prediction
print('Variance score: %.2f' % r2_score(diabetes_y_test, diabetes_y_pred))

# Plot outputs
plt.scatter(diabetes_X_test, diabetes_y_test,  color='black')
plt.plot(diabetes_X_test, diabetes_y_pred, color='blue', linewidth=3)

plt.xticks(())
plt.yticks(())

plt.show()
```

Results

```
Mean squared error: 2548.07
Variance score: 0.47
```



- We have trained a linear regression model on a real dataset.
- Note: mean square error is affected by value range, variance is always comprised between 0 and 1.

HOME PRACTICE

-

END

What about non-linear data?

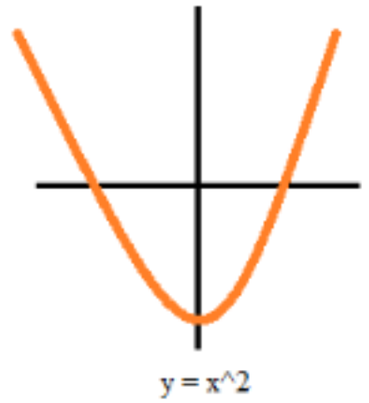
- So far we have seen a regression method that only works if the function from the input variables to the output variable is linear. E.g., with only one input variable x:

$$y = f(x) = wx+b$$

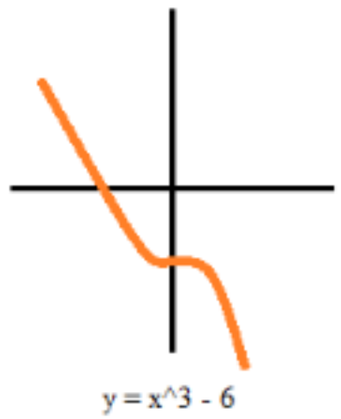
- What if the function is non-linear? The associated expression would be like:

$$y = f(x) = w_1x+w_2x^2+w_3x^3...$$

with a different weight w for each exponential.



Non-linear functions



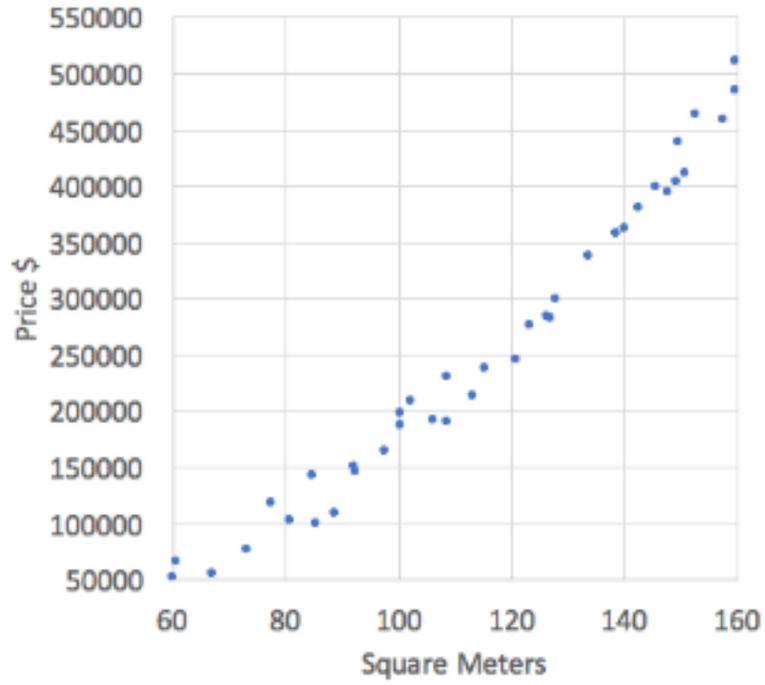
- A simple trick to obtain non-linearity is to artificially generate new features:
  - We start from a feature x_1
  - We can compute the feature x_1^2 and add this new feature to our data
  - We then compute the feature x_1^3 and add it to the data
  - And so on...

Example: house prices

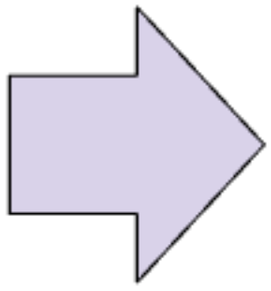
- Let's suppose that the price is a non-linear function of the size in square meters.
- In this example, the function that relates the price to the size is:

  $$\text{Price} = 0*\text{Size} + 20*\text{Size}^2 + 0$$

- We kept the zeros to show all the coefficients and variables.
- We can model the above function by augmenting our dataset as follows:



Size (sqm)	Price
60	63193.69799
65.04312529	70911.59045
68.8814367	80082.32417
69.35554098	80602.04965
69.73350476	114729.8332
74.53091304	131513.3546
78.11717167	108655.0616



Size (sqm)	**Size^2**	Price
60	**3600**	63193.69799
65.04312529	**3887.220733**	70911.59045
68.8814367	**4436.82399**	80082.32417
69.35554098	**4764.013352**	80602.04965
69.73350476	**5225.380597**	114729.8332
74.53091304	**5321.441446**	131513.3546
78.11717167	**5993.666987**	108655.0616

Limits and advanced methods

- There are limits to the previous “trick”:
  - We have to **manually** add features before training
  - We don’t know where to **stop**
    - to which degree of the polynomial? x^3? x^4? x^{20} ?
    - How about products of features like x_1x_2 or $x_1^2x_2^3x_2^2$?
  - There can be so many features that this would make dimensionality (number of features) to explode.

- After presenting the basic approach to classification we will describe **more advanced methods** for regression.
- Those methods do not need to manually add features but have different ways of coping with non-linearity.

Classification

- The classification problem ask to predict a categorical variable's value from the values of other variables.
- Easiest example is with two variables x and y:
  - x is the variable in input
  - y is the variable we want to predict

x	y
1	A
2	A
3	B
4	B
5	A

Training data: x is the input data, y is the label data.

Learning

Learning task: **what's the mapping from x to y?**

Testing

Try to "learn" from the training data an hypothesis function h.

What is h(6)? That is, what's y when x is 6?

x	y
6	?

Classification example 1/2

- We have again the data from 10 thousand houses in the U.S.

City	Rooms	SQM	Price
Los Angeles	3	130	420000
Los Angeles	2	60	380000
...	...	...	...
Albuquerque	2	140	220000
Albuquerque	3	150	250000

- **Goal:** learn a function (model) that can infer the City given all the other variables, for houses not in the 10 thousand dataset:

Price	Rooms	SQM
700000	5	230

City
?

Classification example 2/2

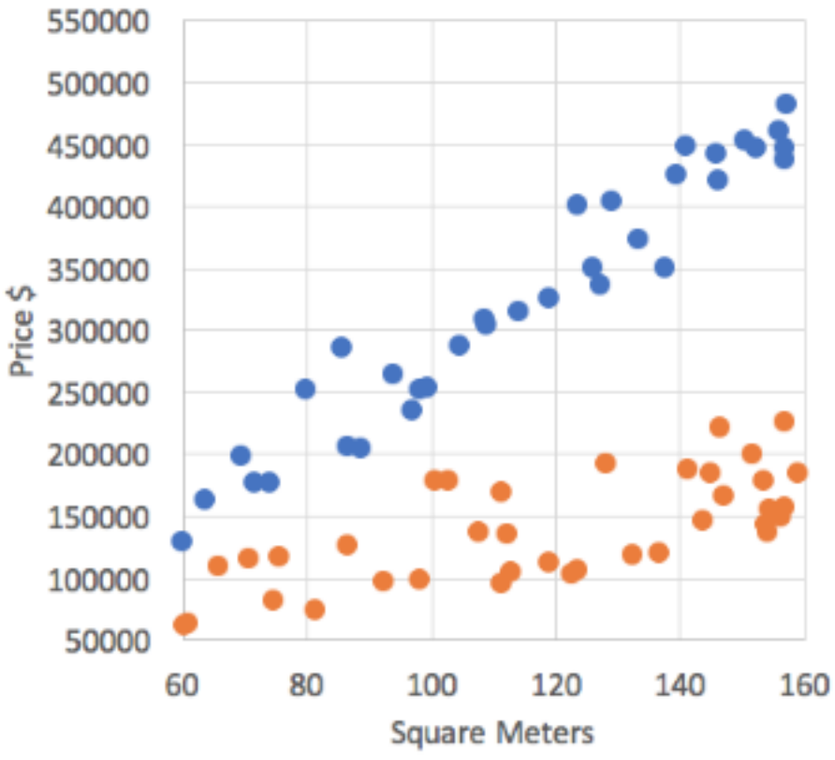
- The houses' prices can be an example of **classification** task:
  - Among the variables we choose the output variable (City)
  - The output variable is the ground truth, because it's the actual city of the house.
  - The output variable we want to predict is a categorical value

Price	Rooms	SQM
700000	5	230

→

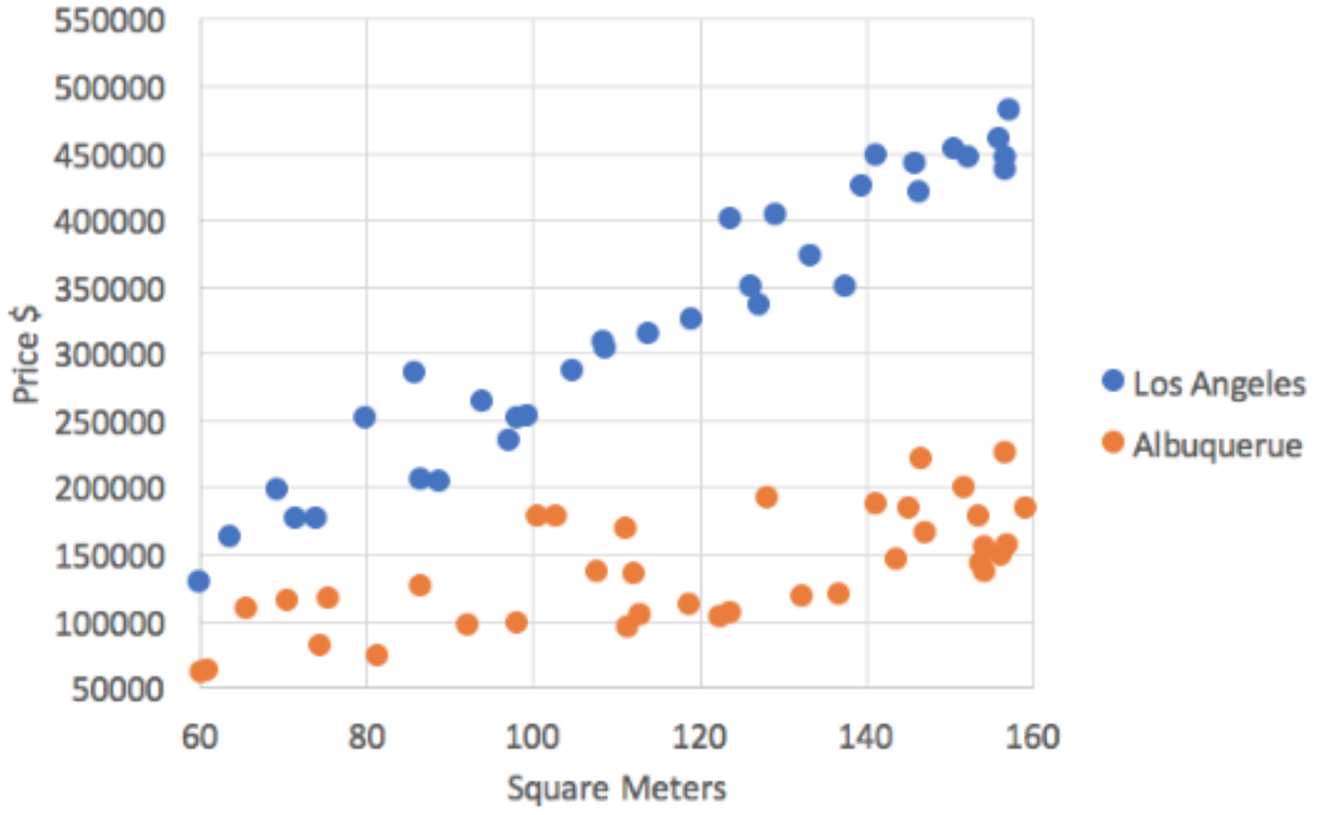
City
?

- To visualize things better we will have examples with two variables (no rooms) as input and one as output
- The categorical output will be visualized using a **different color for each category**



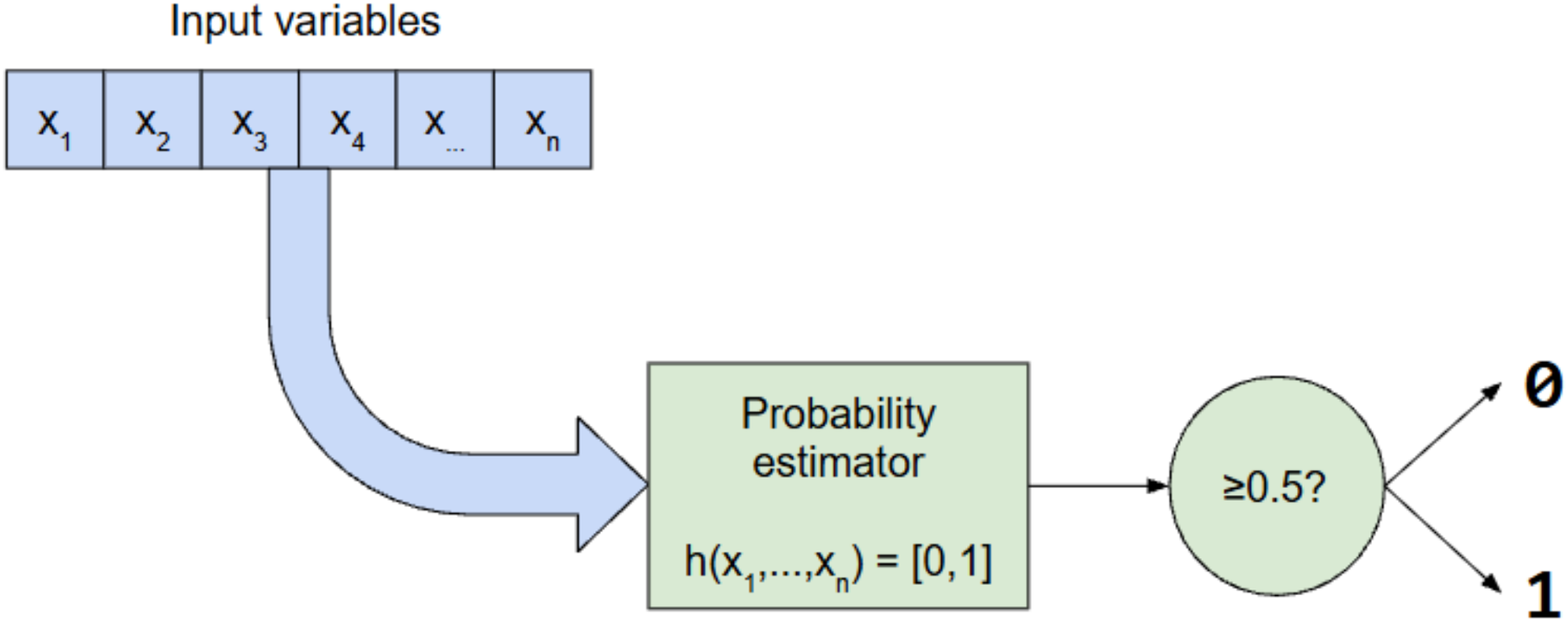
Binary classification

- The binary classification is the task of classifying between two classes.
- For example:
  - Detecting if an email is spam or not
  - Deciding if an image has a cat in it
  - Predicting if a currency will go up or down
  - Classifying if a house is in L.A. or Albuquerque



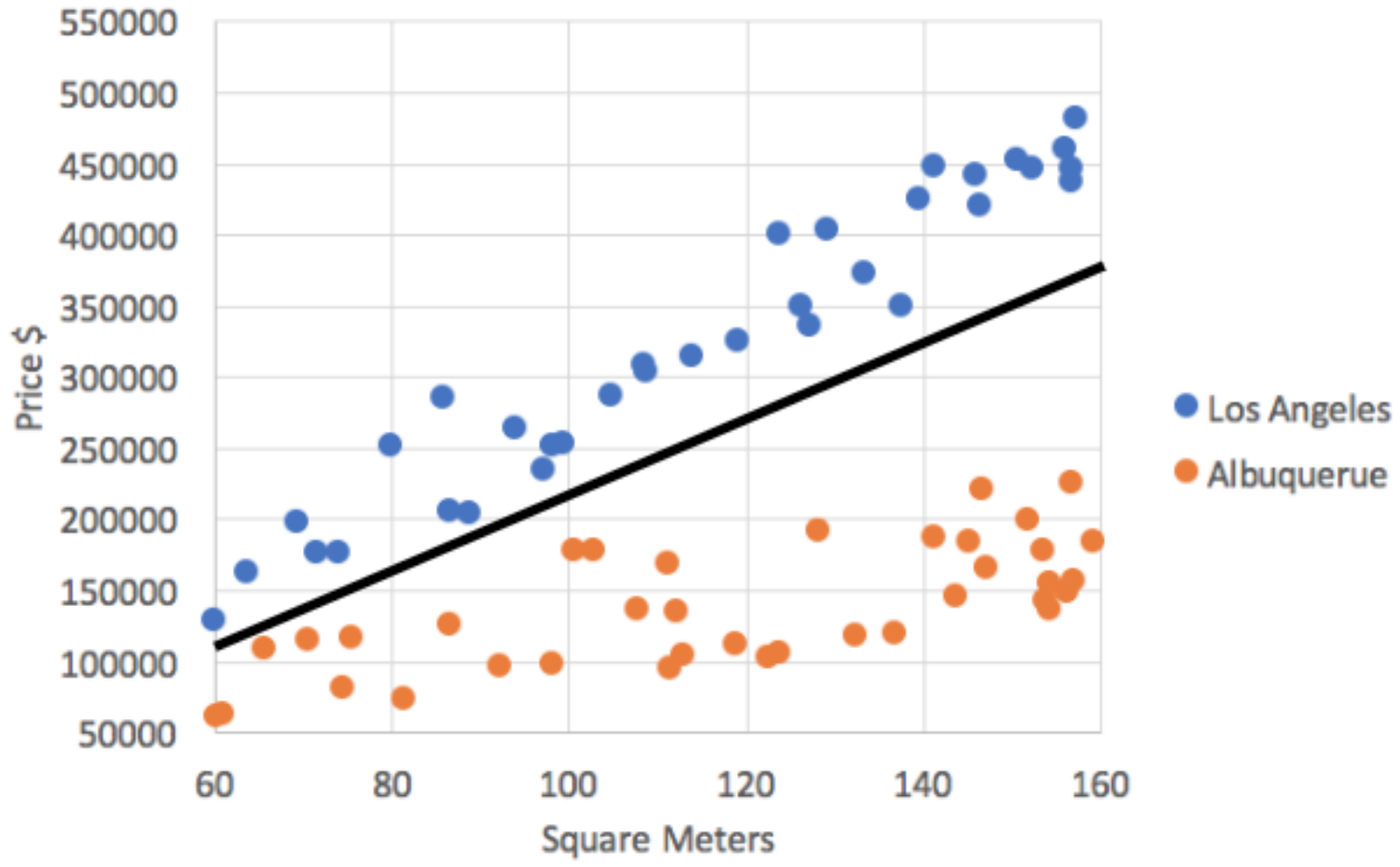
Binary classifier prediction

- A binary classifier prediction works as following:
  - Estimate a score of probability for the first class
  - Output a binary value:
    - 1 if the probability score is greater than or equal to 0.5
    - 0 if the probability score is less than 0.5



Separating the space

- Visually speaking, it is very easy to linearly separate (i.e. with a straight line) the space between Los Angeles houses and Albuquerque houses:



- But how could we **learn** a function that separate the space automatically?

Linear regression for classification?

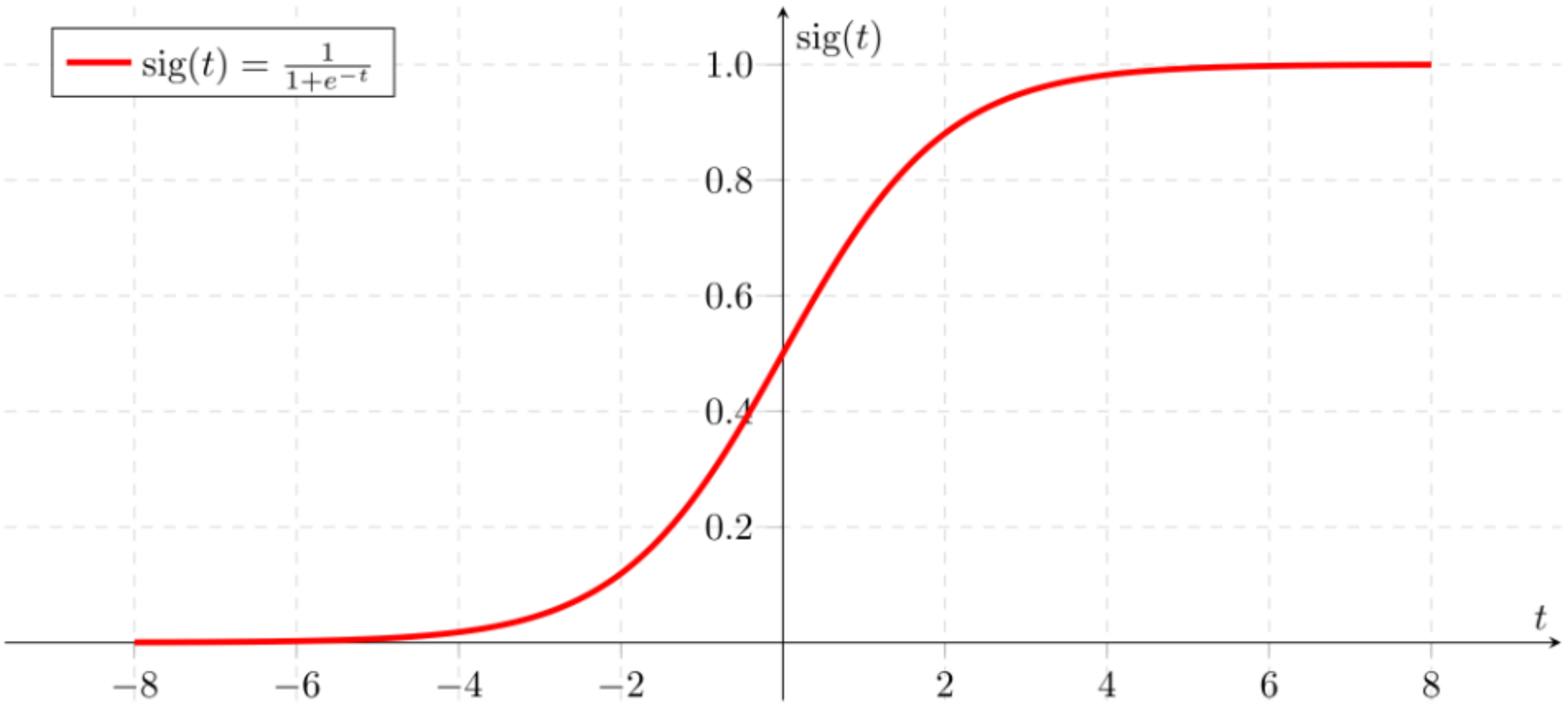
- In the case of classification, our hypothesis is a function that serves as a probability estimator
  - It takes the variables in input (e.g. house size and price)
  - It must outputs **a value between 0 and 1**

- Can we use **linear regression**? After all...
  - ...the output value is actually numerical: 0 or 1
  - ...the line that separates our examples is a straight line

- **Problem:** we don't have control over unseen data, so we could have values bigger than 1, or lower than 0.
- **Idea:**
  - We use a linear function to combines all the input variables into a value
  - We apply a function to constrain every possible value into a range of [0,1]

Logistic (sigmoid) function

- The ***sigmoid*** function is a special case of the **logistic function**.
- Sigmoid functions have domain of **all real numbers**, with return value monotonically increasing **from 0 to 1**.



Logistic Regression

- Despite the name, the logistic regression is actually a **classification** method.

- Recall the linear regression hypothesis was a linear combination of the input variables, with one weight for each variable:

$$h_{linear}(x_1,...,x_n) = w_1x_1+...+w_nx_n+b$$

- Its hypothesis function is simply the sigmoid function applied to the linear combination:

$$h_{logistic}(x_1,...,x_n) = sig(w_1x_1+...+w_nx_n+b)$$

Logistic Regression: loss function

- Recall that we need a loss function to **tune the weights towards a minimum loss**.
- We have a training input x. We consider two cases:
  - **When the true y is 0**: the hypothesis should output 0, anything more than 0 is a loss! So we can use simply the hypothesized score.

$$\text{loss}(x) = h_{\text{logistic}}(x)$$

  - **When the true y is 1**: the hypothesis should output 1, anything less than 1 is a loss! So we can use the difference between 1 and the hypothesized score.

$$\text{loss}(x) = 1 - h_{\text{logistic}}(x)$$

Interpreting the weights

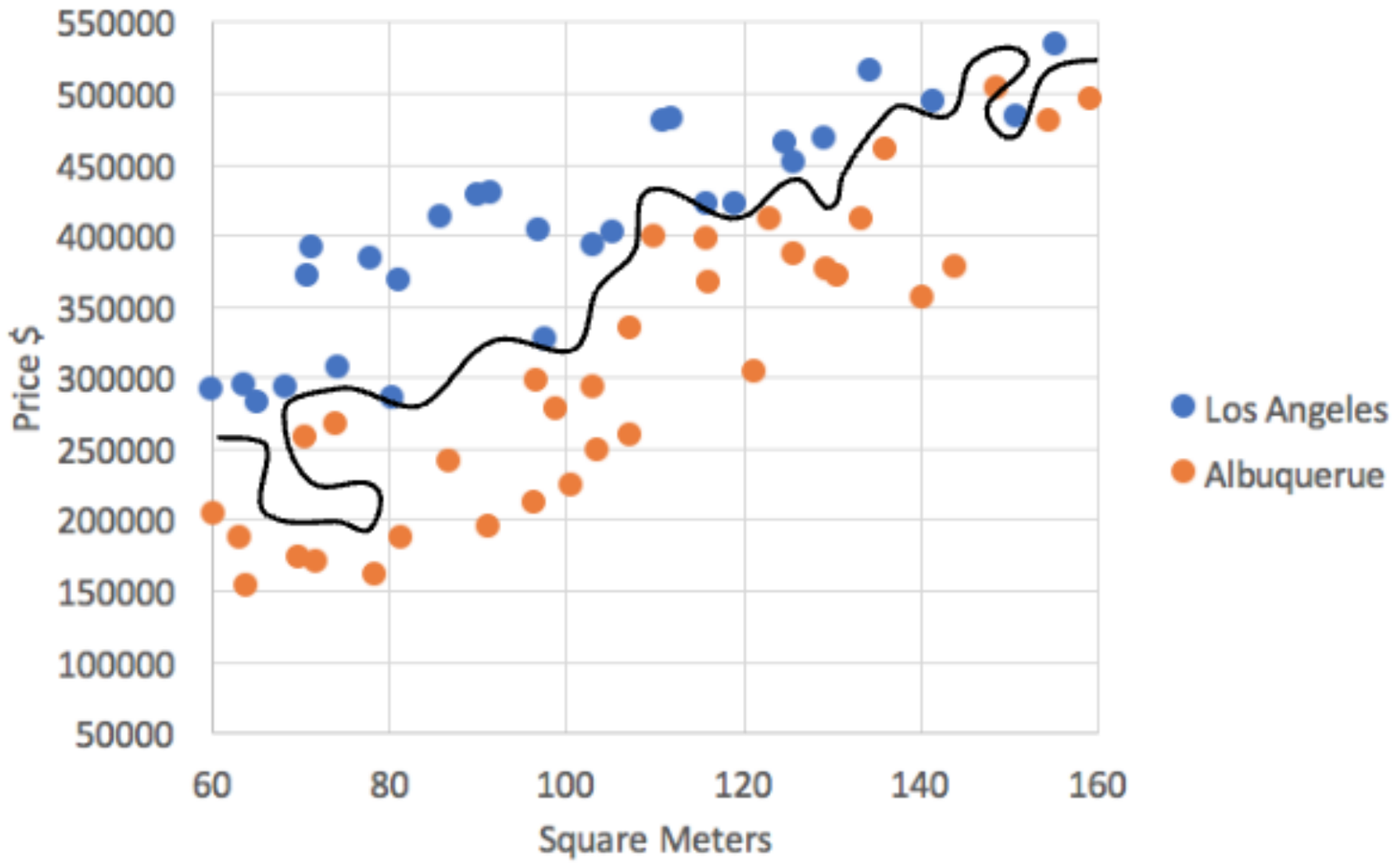
- An advantage of logistic regression over more complex models (e.g. neural networks) is that an **hypothesis can be easily described** and understood.
- Suppose that our data is all scaled in the same range (e.g. [0,1]), and we have the usual hypothesis:

$$h_{logistic}(x_1,...,x_n) = sig(w_1x_1+...+w_nx_n+b)$$

- Then, each weight w_i tells us **how important** the variable x_i is in predicting the positive class (i.e. in predicting “1”)
- Why?
  - Intuitively, if a weight is high, the associated variable will strongly contribute to the sum, which is proportional to the probability score.
  - If otherwise a weight is close to 0, the associated variable is not taken in consideration when computing the probability score.

Problem: Overfitting 1/2

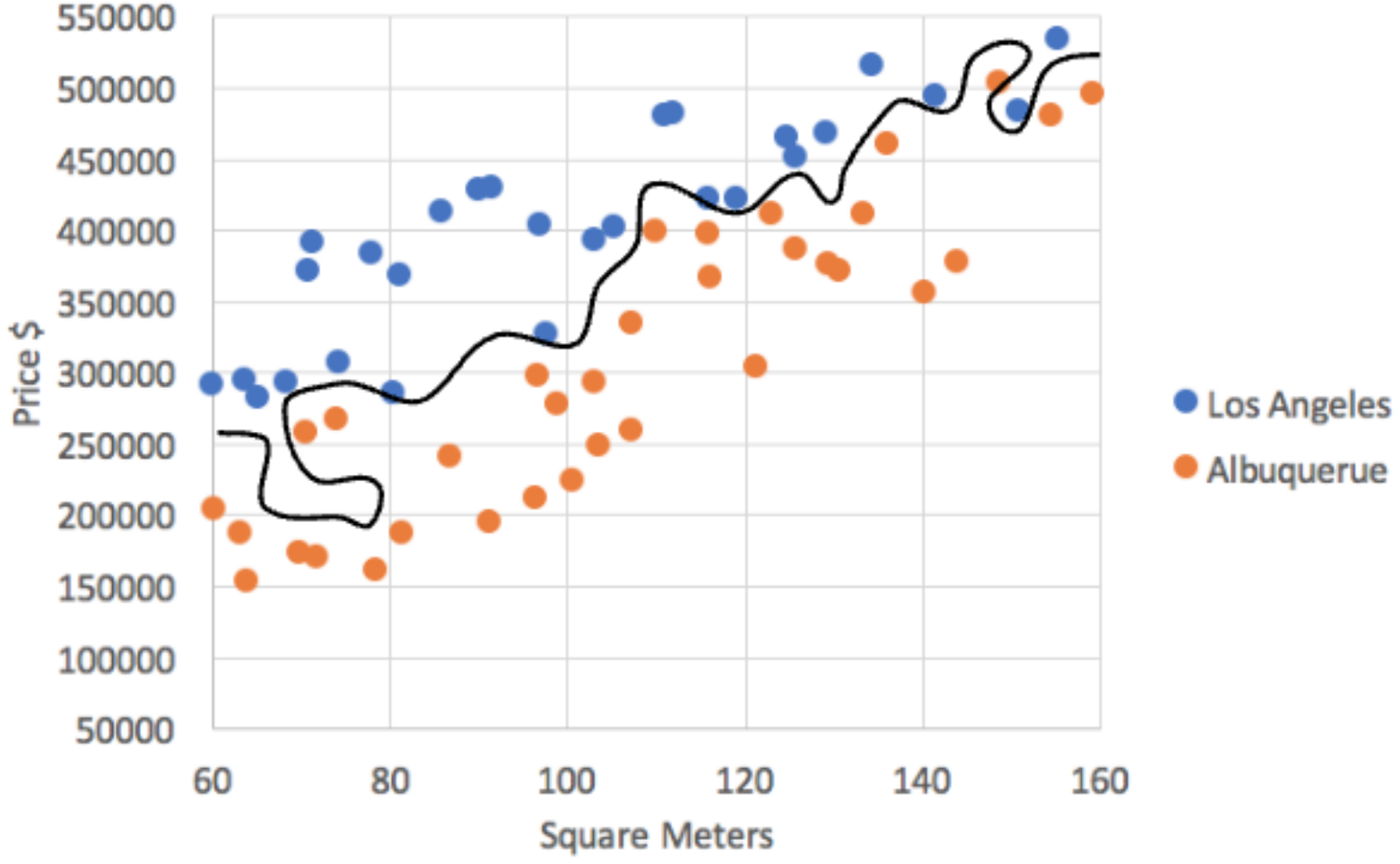
- Using the **same trick** of introducing artificial features using polynomials of different degrees (e.g. $x_1^2 x_2^3 x_2^2$...), we could train a very complex non-linear function:



- **Is this a good thing?** For sure it's perfect for the training set… what about **unseen data**?

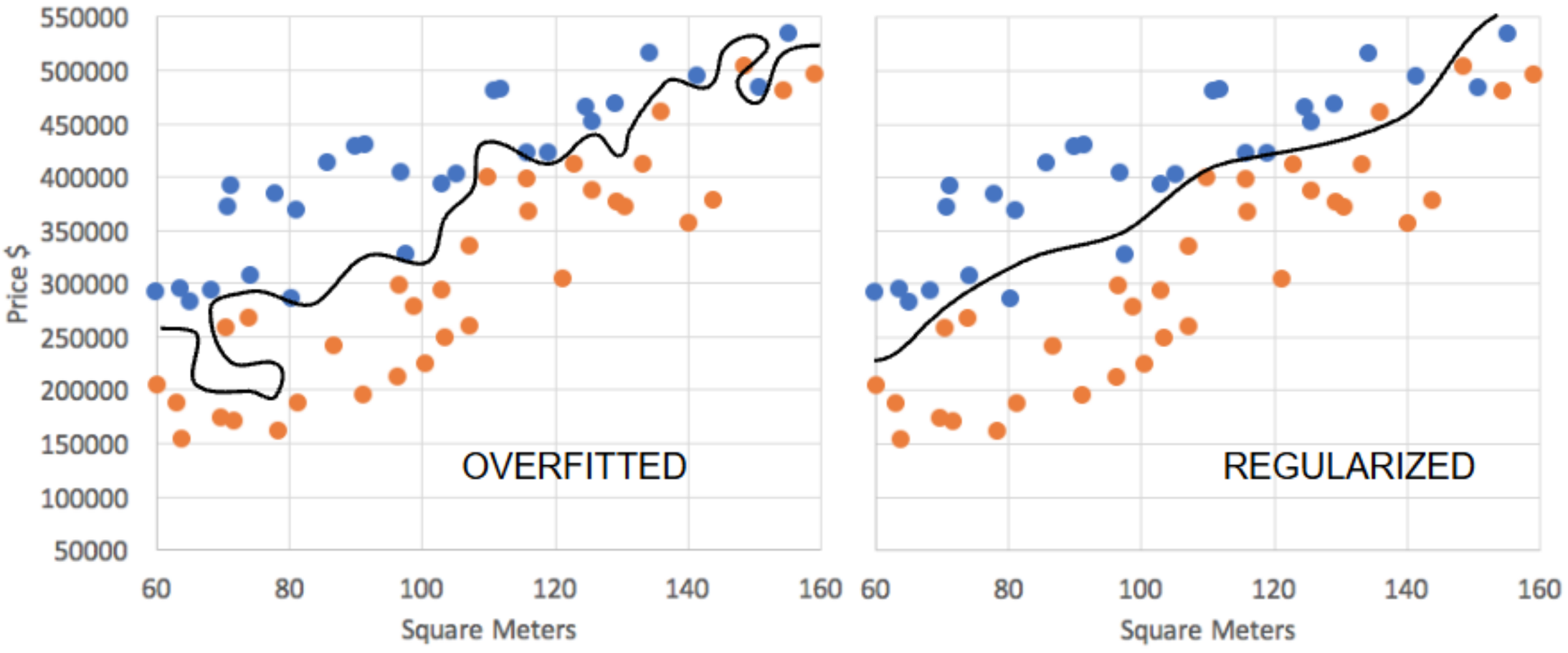
Problem: Overfitting 2/2

- It turns out it is actually not good: the model is **overly fitted** on the training set the unseen data could fell randomly on one side or the other.
- The model should be more robust and **generalized** to work also on unseen data (such as the testing set).



Solution: Regularization

- Regularization is a very effective technique to prevent overfitting
  - It's a modification of the loss function.
  - We add an additional value to the loss function that increases as the value of features weights (w) increase.
- What is the effect of regularization?
  - It prevents the features weights (w) to be very large
  - Visually speaking, it will "smooth" the decision boundary line:



Multi-class classification

- Binary classification **can be generalized** to multi-class classification
- There are **two ways** to adapt binary classifiers to a **K-classes** classification problem:
  - **OVO - One vs. One**: Each possible pair of classes is taken in consideration to train a different classifier. This approach will **need to train K*(K-1)/2 classifiers**!
  - **OVA - One vs. All** (more common): for each class, a different classifiers is trained to distinguish between that class and all the other classes merged together. This approach will **need to train only K classifiers.**

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BEGIN

Used software: Jupyter, Sci-kit Learn
Find them in the Anaconda package here: https://www.anaconda.com/

Jupyter demo: Iris dataset

- Introduce in 1936, the **Iris dataset** is the “Hello World” of classification: it is commonly used as a simple example of **multi-class** classification problem.
- It has **3 classes** of Iris **flowers**:

Iris Versicolor

Iris Setosa

Iris Virginica

Dataset features

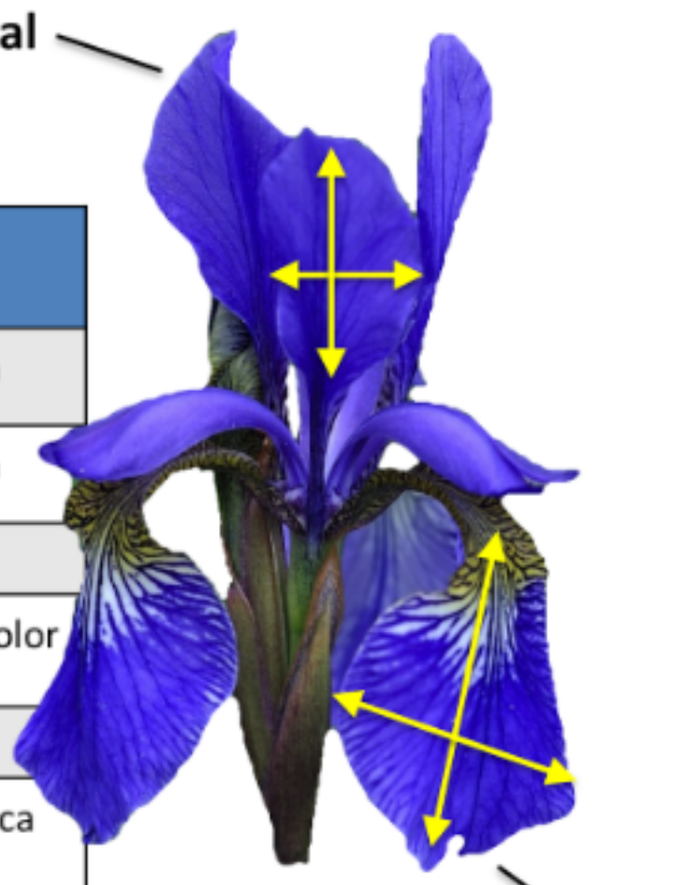
- We will apply **Logistic Regression** with **regularization** on the iris dataset:

Samples
(instances, observations)

	Sepal length	Sepal width	Petal length	Petal width	Class label
1	5.1	3.5	1.4	0.2	Setosa
2	4.9	3.0	1.4	0.2	Setosa
...					
50	6.4	3.5	4.5	1.2	Versicolor
...					
150	5.9	3.0	5.0	1.8	Virginica

Features
(attributes, measurements, dimensions)

Class labels
(targets)



Import dataset

Logistic Regression on the iris dataset

We will train a logistic regression model using gradient descent and OVA approach for multi-class classification.

First of all we import numpy library to hand vectors and matrices, matplotlib to plot the decision boundaries, and scikit learn to get the dataset and the gradient descent algorithm.

In [5]:
```
%matplotlib inline
import numpy as np
import matplotlib.pyplot as plt
from sklearn import datasets
from sklearn.linear_model import SGDClassifier

# import the data to play with
iris = datasets.load_iris()
```

Our iris dataset has several examples and features, let's see them:

In [6]:
```
print(iris.data.shape)
print(iris.feature_names)
```

```
(150, 4)
['sepal length (cm)', 'sepal width (cm)', 'petal length (cm)', 'petal width (cm)']
```

To keep things simple and be able to plot examples in a 2D plane, we will use only the first two features: the sepal length and the sepal width.

Dataset content

To keep things simple and be able to plot examples in a 2D plane, we will use only the first two features: the sepal length and the sepal width.

In [9]:
```
# we only take the first two features.
X = iris.data[:, :2]
y = iris.target
colors = "bry"

print(y)
print(iris.target_names)
```

```
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 2 2 2 2 2 2 2 2 2 2
 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
 2 2]
['setosa' 'versicolor' 'virginica']
```

So our target variable *y* has the labels 0, 1 and 2 depending on the class of flower: 0 is setosa, 1 is versicolor and 2 is virginica. The examples are sorted by class. Because we are going to use *stochastic* gradient descent, which updates the weights one example at a time, it's better to shuffle our examples.

In [11]:
```
# shuffle
idx = np.arange(X.shape[0])
#setting the randomizer seed allows us to
#have reproducibility of the experiment!
np.random.seed(13)
np.random.shuffle(idx)
X = X[idx]
y = y[idx]
```

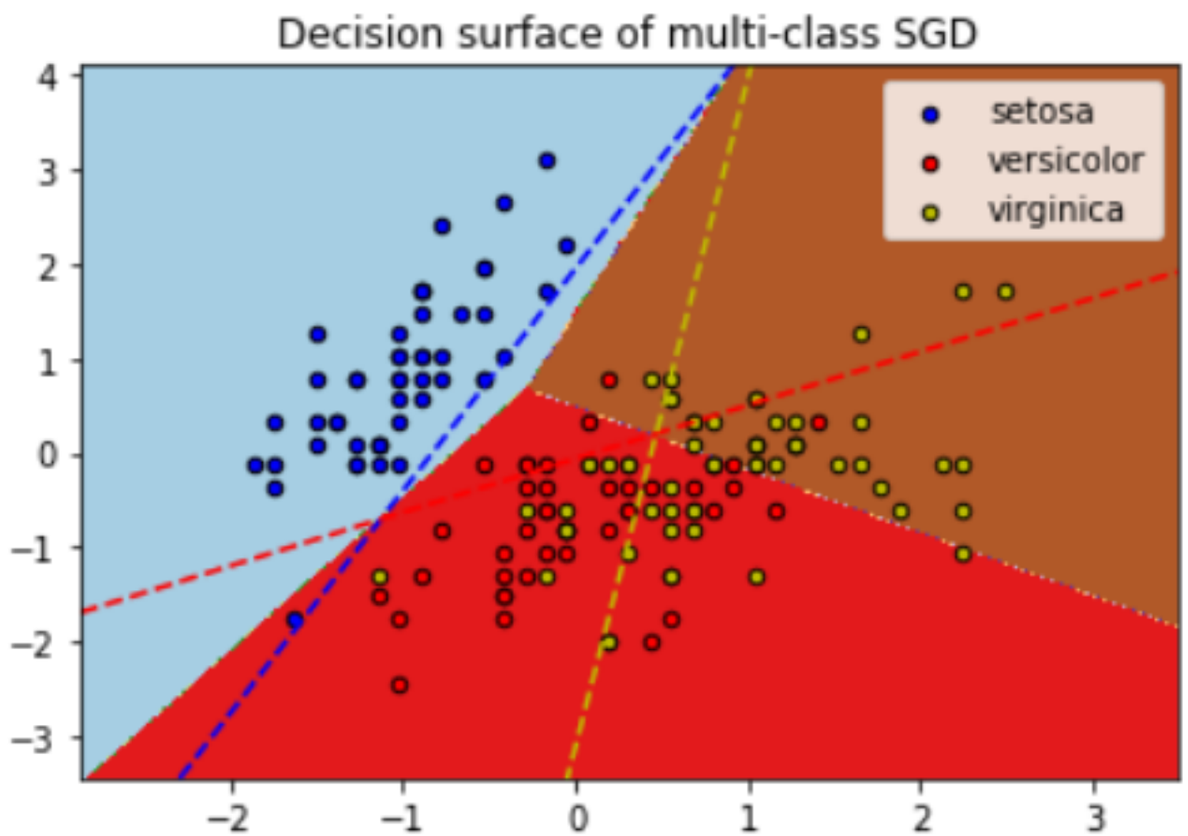
Training

Now we standardize the data, centering it to a 0 mean, to make the optimization (gradient descent) faster.

In [17]:
```
# standardize
mean = X.mean(axis=0)
std = X.std(axis=0)
X = (X - mean) / std

#Train!
clf = SGDClassifier(alpha=0.00001, max_iter=100).fit(X, y)
```

Let's visualize the decision boundaries (not going into details of how) -> more details in the Jupyter notebook.



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END

Summary

- We have seen the two most popular methods for regression and classification:
  - **Linear regression** (regression): is trained to predict a numerical value
  - **Logistic regression** (classification): is trained to predict a class
- These methods and the related optimization technique are **basis** for much more complex ML algorithms such as **Neural Networks**.

- What's next in the supervised methods?
  - **Distance-based**: k-NN, SVM, Centroid classifiers
  - **Trees and forests**: decision trees, random forests, gradient-boosting decision trees
  - **Deep learning**: Neural networks and word embeddings

References

Stanford Lectures on Machine Learning

Author: Andrew Ng

Find the **Jupyter** notebook used in these Slides in the ***Notebooks* folder** of the Complements of Databases Google Drive shared folder:

goo.gl/Lqn3ov