HPE DSI 311
Introduction to Machine Learning

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Overview

- Simple models to get started:
  - K nearest neighbors
  - Logistic Regression
- Hands-on examples
  - Jupyter Notebooks
  - Data Summarization

ML techniques: How do they differ?

ML techniques by data type

Unsupervised: aims to uncover groups of observations from initially unclassified data

Analyze: How is the data set X structured?

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Analyze: How is the data set X structured?

Supervised: works with data that is already classified to tailor rules for classifying new (and as yet unclassified) individuals; no feedback

Predict: What would the data point x do?

ML techniques by data type

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Predict: What would the data point x do?

Reinforcement learning: the problem faced by an agent that learns behavior through trial-and-error interactions with a dynamic environment

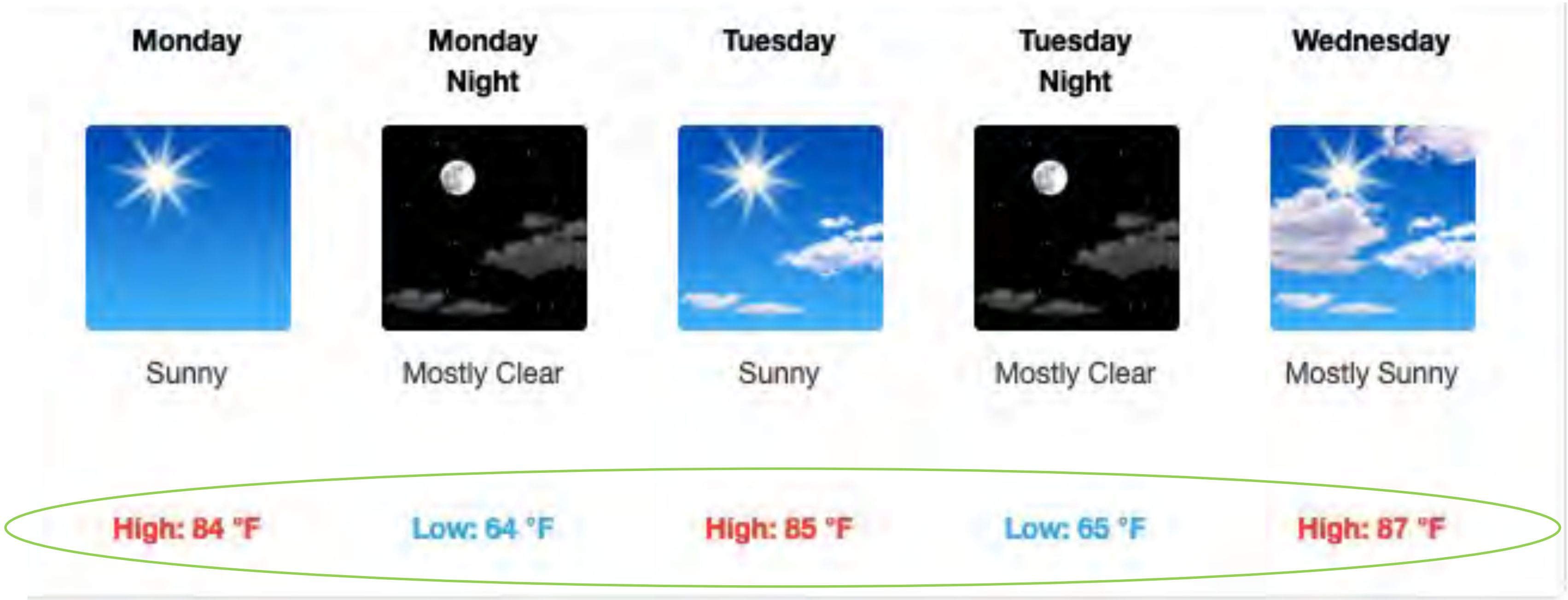
Gameify: Faced with (X,Y), which strategy wins?

ML techniques by data type

Unsupervised	Supervised	Reinforcement Learning
Clustering / Anomaly detection	Classification/ Regression	Dynamic Programming (Monte Carlo, genetic algorithms)
Signal Separation (matrix factorization)		Deep RL

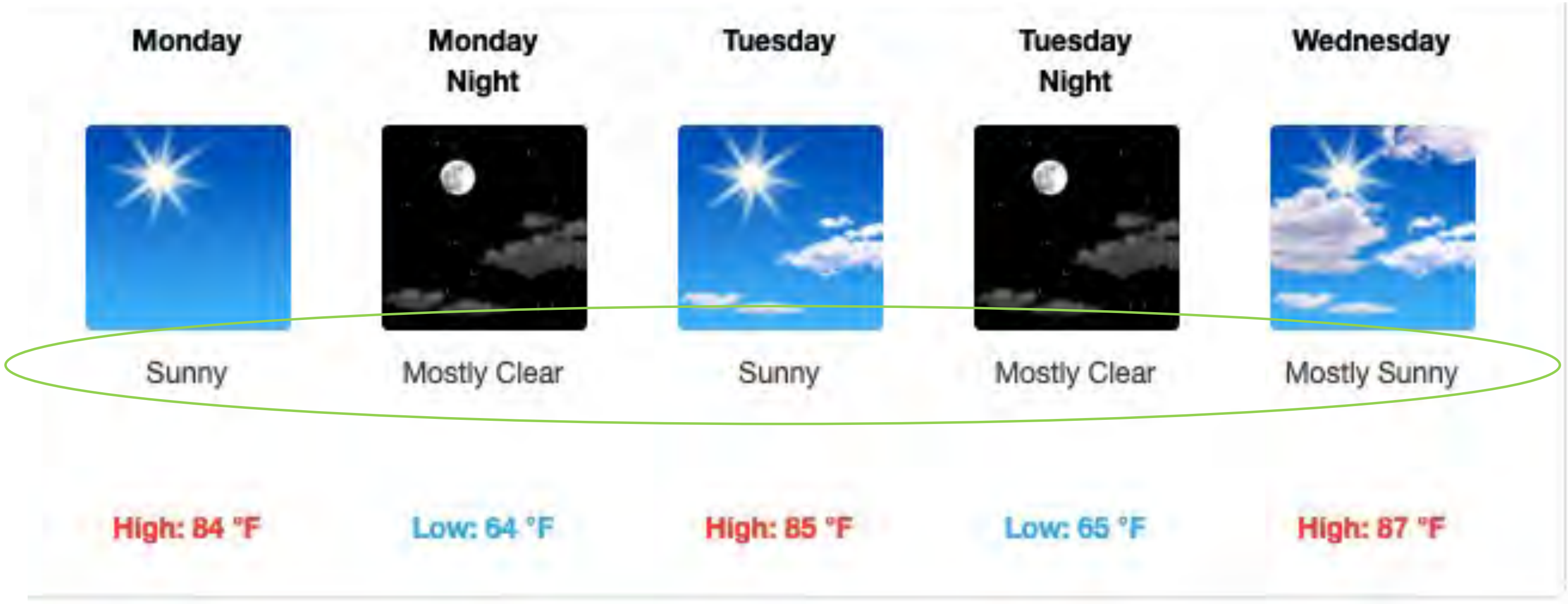
What types of classification problems?

Supervised ML



Regression:
predict a number

Supervised ML



Classification: predict a label

Regression: predict a number

Classification using K Nearest Neighbors

K-Nearest Neighbors: algorithm

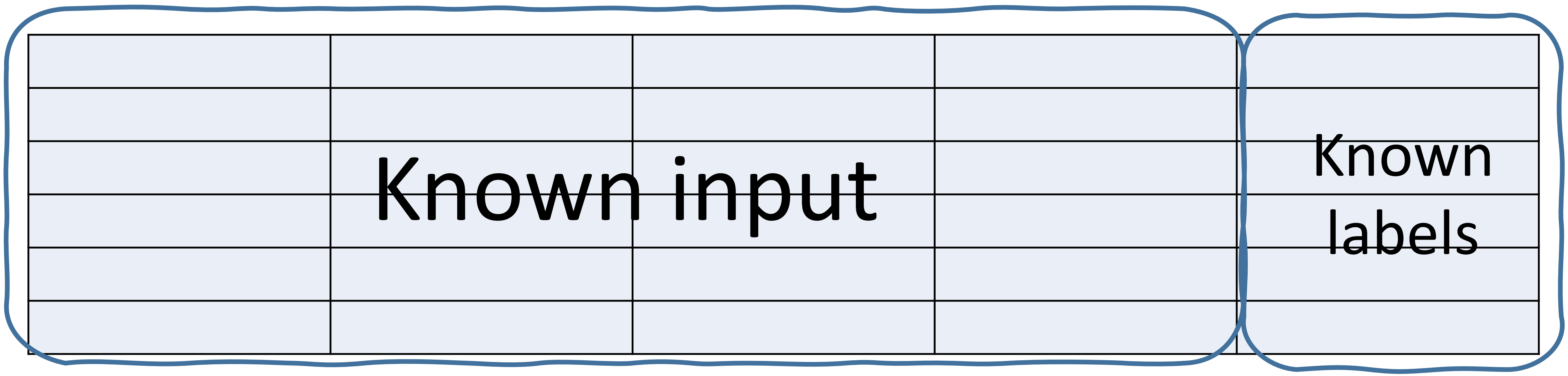
Training algorithm

- All training example points (*x_train, y_train*) go into a reference list

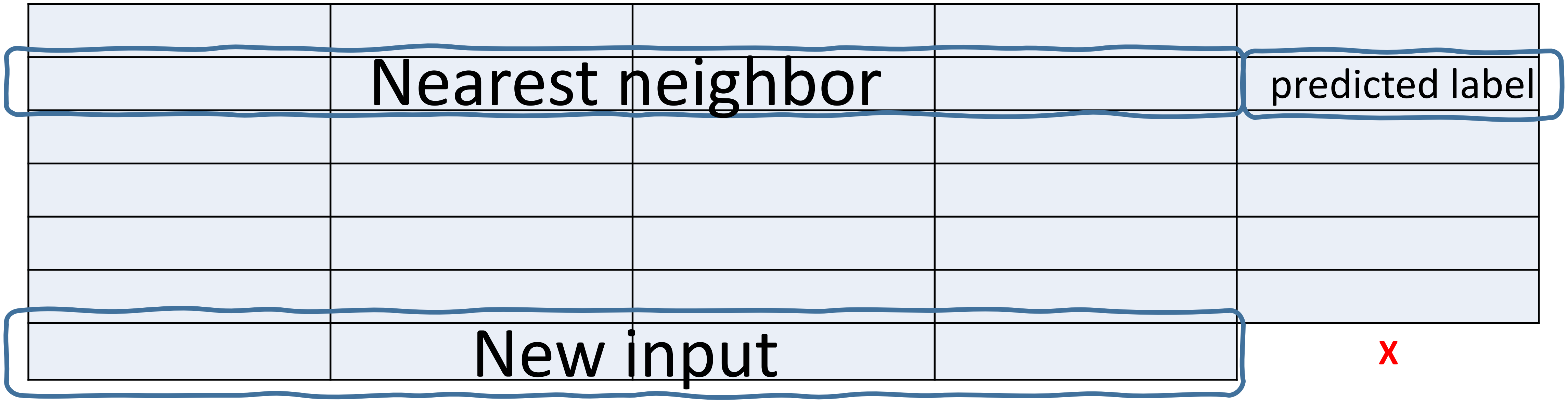
Classification algorithm

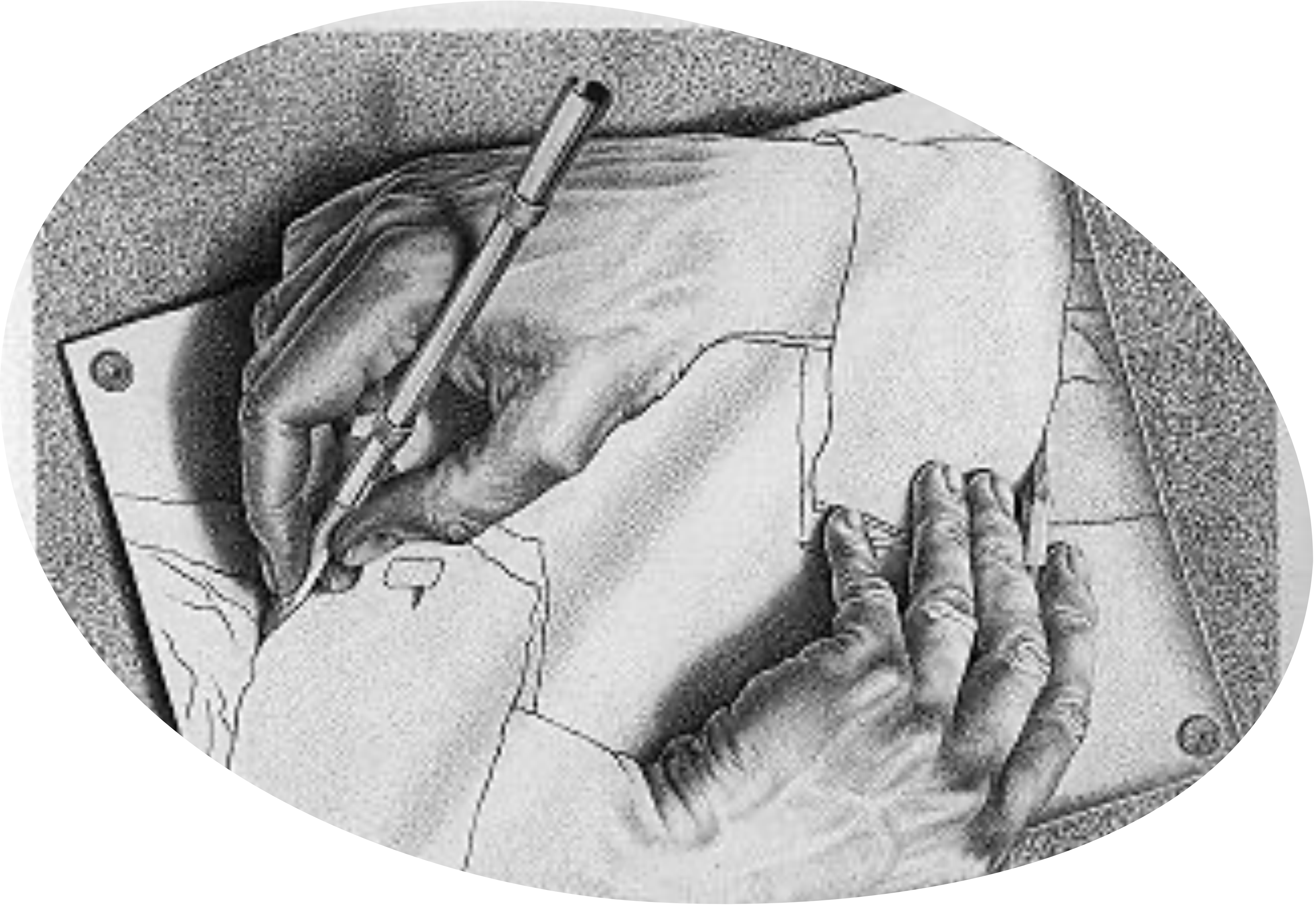
- Given a query instance *x_test* to be classified, find the **nearest** point *x_train* in the reference list
- Repeat until **k nearest points** are identified from the list
- Calculate *y_predict* based on the values of *y_train* for these neighbors, i.e., k nearest points

In practical terms: training



In practical terms: prediction





Hands-on Example:

k-NN

K-Nearest Neighbors: sklearn implementation

KNeighborsClassifier(*n_neighbors=5,*
weights='uniform',
algorithm='auto',
leaf_size=30,
p=2,
metric='minkowski',
metric_params=None,
n_jobs=None,
***kwargs*)

https://scikit-learn.org/stable/modules/generated/sklearn.neighbors.KNeighborsClassifier.html

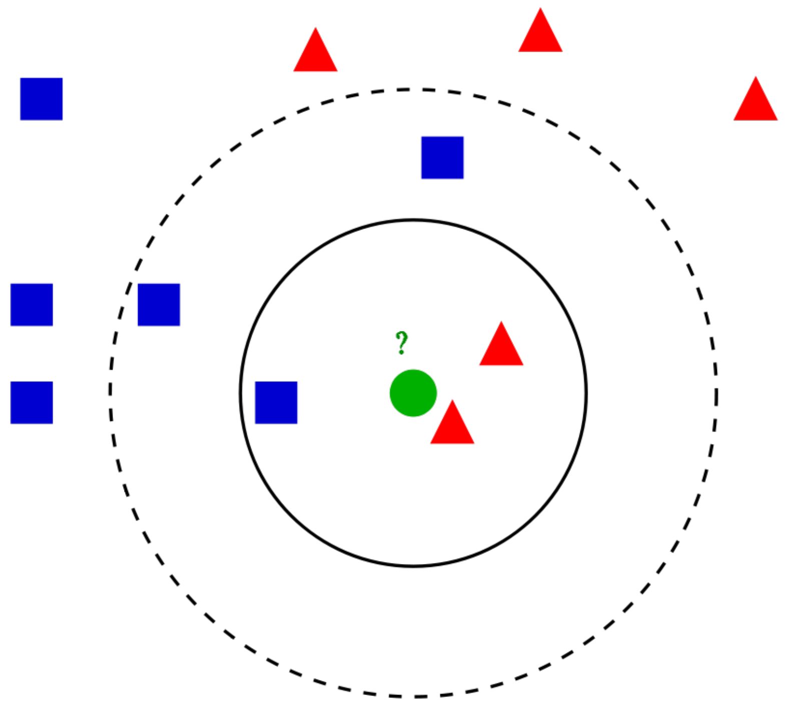
K-Nearest Neighbors: choice of K

KNeighborsClassifier(***n_neighbors***=*5*,
weights='uniform',
algorithm='auto',
leaf_size=30,
p=2,
metric='minkowski',
metric_params=None,
n_jobs=None,
***kwargs*)

K-Nearest Neighbors: choice of K

Who are the neighbors of the new sample (green circle)?

Blue squares or red triangles?



$$g(\mathbf{x}) = \sum_{i \in \mathrm{kNN}(\mathbf{x})} y_i$$

- k = 1: a RED TRIANGLE is the nearest neighbor, so the guess would be RED TRIANGLE
- k = 3 (solid line circle): 2 red triangles and only 1 blue square in the neighborhood, so the guess would be RED TRIANGLE
- k = 5 (dotted line circle): 3 blue squares and only 2 red triangles in the neighborhood, so the guess would be BLUE SQUARE

K-Nearest Neighbors: choice of weight

KNeighborsClassifier(*n_neighbors=5,*
weights*='uniform',*
algorithm='auto',
leaf_size=30,
p=2,
metric='minkowski',
metric_params=None,
n_jobs=None,
***kwargs*)

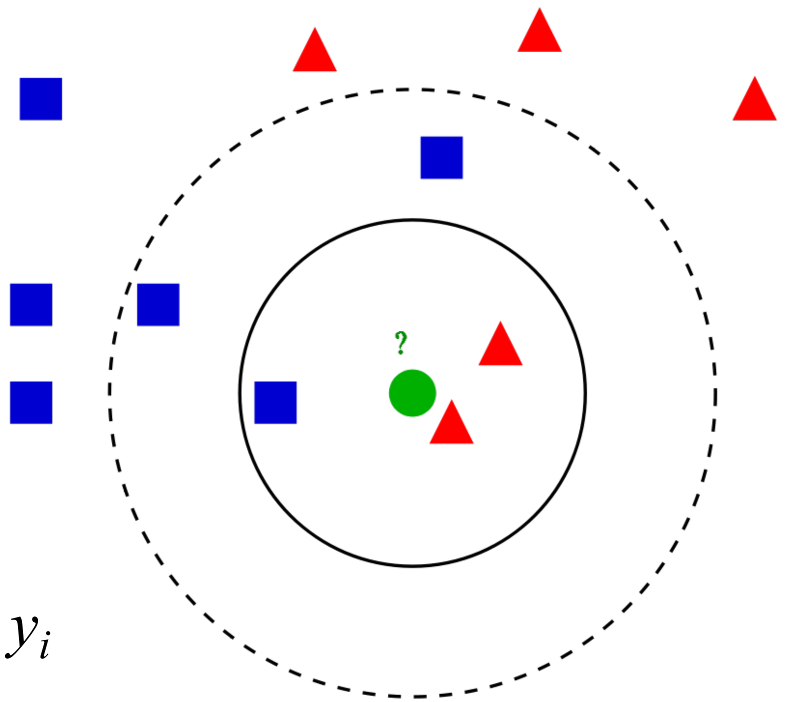
K-Nearest Neighbors: choice of weight

Weights default=’uniform’

weight function used in prediction. Possible values:

- ‘uniform’ : uniform weights. All points in each neighborhood are weighted equally.
- ‘distance’ : weight points by the inverse of their distance. In this case, closer neighbors of a query point will have a greater influence than neighbors which are further away.
- [callable] : a user-defined function which accepts an array of distances, and returns an array of the same shape containing the weights.

K-Nearest Neighbors: choice of weight



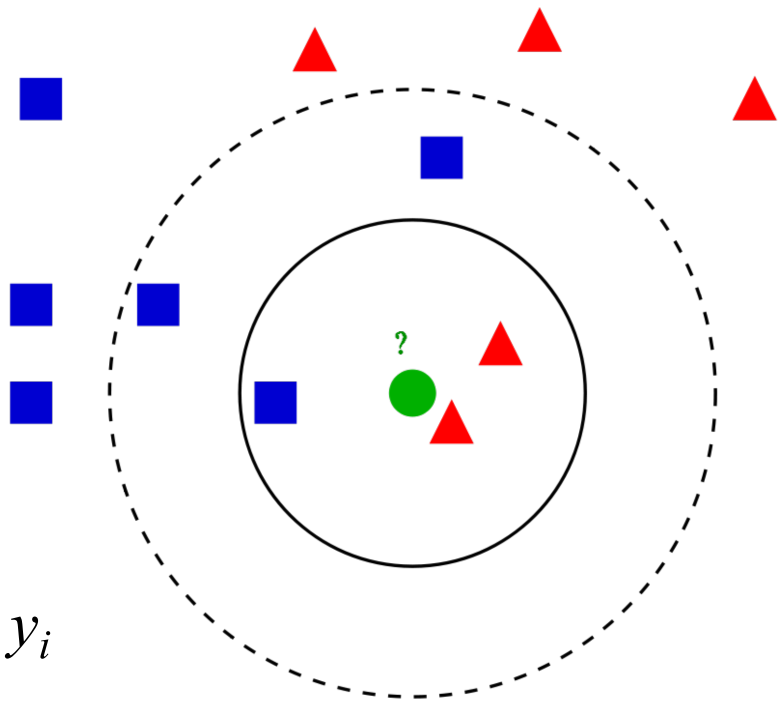
Who are the neighbors of the new sample (green circle)?

Blue squares or red triangles?

$$g(\mathbf{x}) = \sum_{i \in \mathrm{kNN}(\mathbf{x})} weight(\mathbf{x}_i, \mathbf{x})\, y_i$$

Default option for $weight(\mathbf{x}_i, \mathbf{x})$ is uniform (every weight = 1)

K-Nearest Neighbors: choice of weight



Who are the neighbors of the new sample (green circle)?

Blue squares or red triangles?

$$g(\mathbf{x}) = \sum_{i \in \mathrm{kNN}(\mathbf{x})} weight(\mathbf{x}_i, \mathbf{x})\, y_i$$

k = 5:

3 distant blue squares and 2 close red triangles in the neighborhood

- Uniform weights: the guess would be BLUE SQUARE
- Distance weights: the guess would be RED TRIANGLE

K-Nearest Neighbors: choice of **metric**

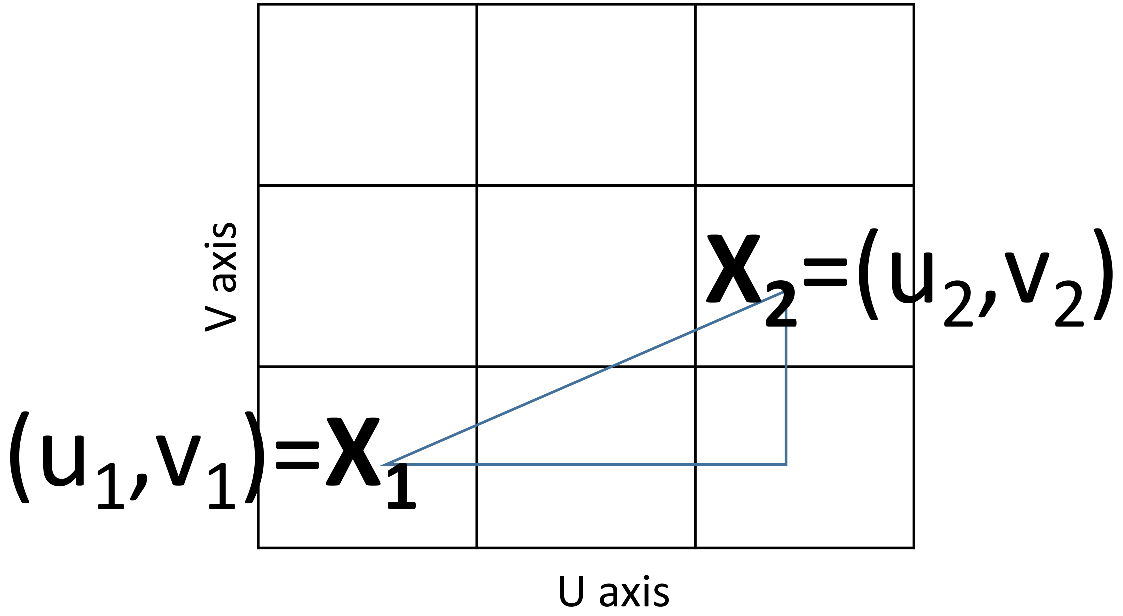
KNeighborsClassifier(*n_neighbors=5,*
weights='uniform',
algorithm='auto',
leaf_size=30,
p=2,
***metric**='minkowski',*
metric_params=None,
n_jobs=None,
***kwargs*)

K-Nearest Neighbors: choice of metric

Dimension(X) = 2

Pythagorean theorem:

$$\{\text{distance}(\mathbf{X_1}, \mathbf{X_2})\}^2$$
$$=$$
$$\{\text{distance\_along\_u\_axis}(\mathbf{X_1}, \mathbf{X_2})\}^2$$
$$+$$
$$\{\text{distance\_along\_v\_axis}(\mathbf{X_1}, \mathbf{X_2})\}^2$$



$$\{\text{distance}(\mathbf{X_1}, \mathbf{X_2})\}^2 = (\mathbf{u_1} - \mathbf{u_2})^2 + (\mathbf{v_1} - \mathbf{v_2})^2$$

Euclidean: As the crow flies

Dimension(X) = 2

Example:

V axis

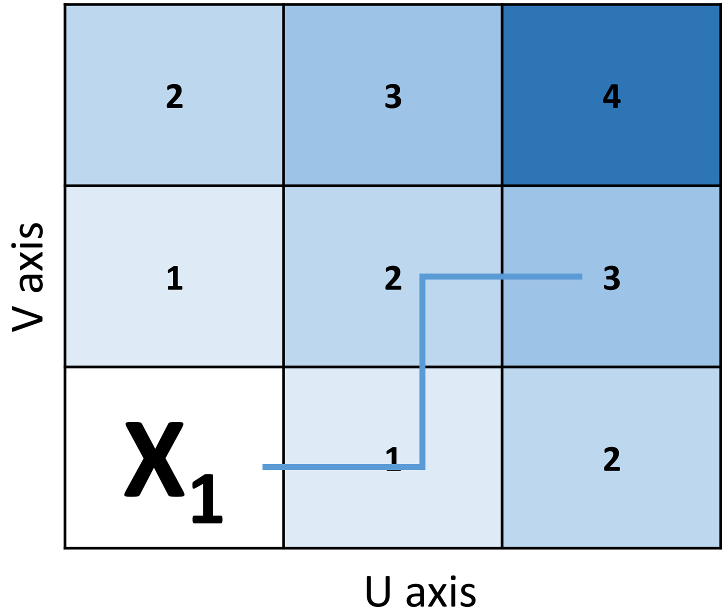
2	2.236	2.828
1	1.414	2.236
X_1	1	2

U axis

Manhattan: As a Lyft drives

$$\text{distance}(\mathbf{X_1}, \mathbf{X_2}) \\ \mathbf{=} \\ \text{distance\_along\_u\_axis}(\mathbf{X_1}, \mathbf{X_2}) \\ + \\ \text{distance\_along\_v\_axis}(\mathbf{X_1}, \mathbf{X_2})$$

Dimension(X) = 2

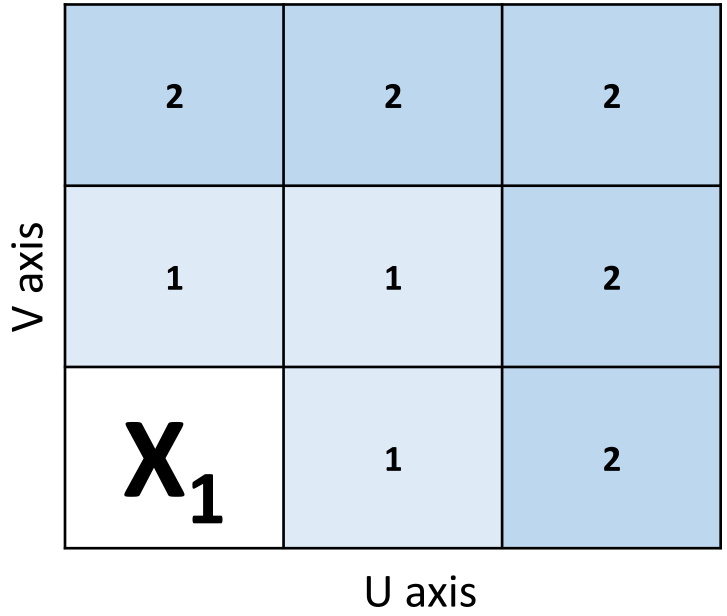


$$\text{distance}(\mathbf{X_1}, \mathbf{X_2}) = |\mathbf{u_1} - \mathbf{u_2}| + |\mathbf{v_1} - \mathbf{v_2}|$$

Maximum Distance

$$\text{distance}(\,\mathbf{X_1}\,,\mathbf{X_2}\,)$$
$$=$$
$$\text{Max}\{\ \text{distance\_along\_u\_axis}(\,\mathbf{X_1}\,,\mathbf{X_2}\,),\ \text{distance\_along\_v\_axis}(\,\mathbf{X_1}\,,\mathbf{X_2}\,)\ \}$$

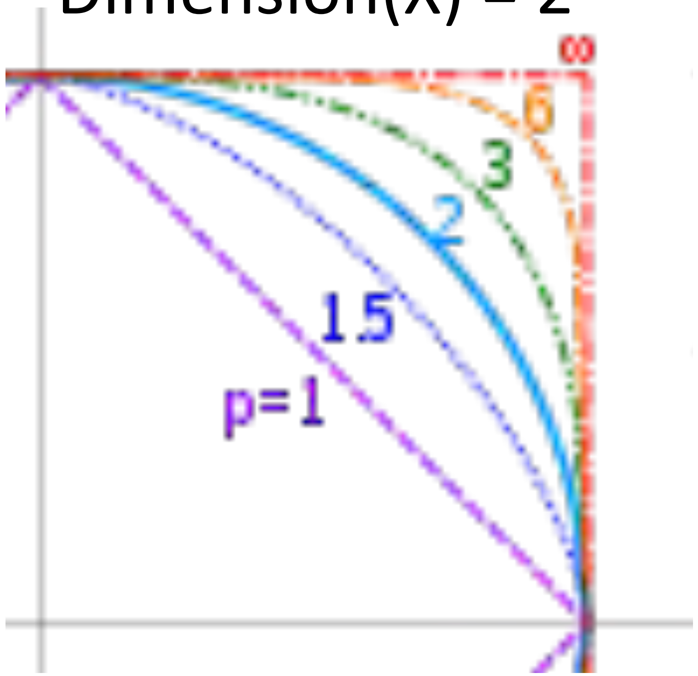
Dimension(X) = 2



Minkowski: The L^p metric

$$\{\, \text{distance}(\, \mathbf{X_1} , \mathbf{X_2} \,)\, \}^p$$
$$=$$
$$\{\, \text{distance\_along\_u\_axis}(\, \mathbf{X_1} , \mathbf{X_2} \,)\, \}^p$$
$$+$$
$$\{\, \text{distance\_along\_v\_axis}(\, \mathbf{X_1} , \mathbf{X_2} \,)\, \}^p$$

Dimension(X) = 2



p = 2: Euclidean – Each point on blue arc is same distance from LL corner

p = 1: Manhattan – Each point on violet diagonal is same distance from LL corner

$p = \infty$: Maximum – Each point on red sides is same distance from LL corner

Minkowski: The L^p metric

Metric is the choice of distance for finding the nearest neighbors. The default metric is minkowski with p=2, which is equivalent to the standard Euclidean metric.

P Power parameter for the Minkowski metric.

- When p = 1, this is equivalent to using manhattan_distance (l1)
- When p=2, this is euclidean_distance (l2)
- For arbitrary p, it is minkowski_distance (l_p)

K-Nearest Neighbors: choice of algorithm

```
KNeighborsClassifier(n_neighbors=5,
weights='uniform',
algorithm='auto',
leaf_size=30,
p=2,
metric='minkowski',
metric_params=None,
n_jobs=None,
**kwargs)
```

K-Nearest Neighbors: choice of algorithm

Algorithm default=’auto’

Algorithm used to find the nearest neighbors:

- ‘ball_tree’ will use a BallTree algorithm
- ‘kd_tree’ will use a KDTree algorithm
- ‘brute’ will use a brute-force search
- ‘auto’ will attempt to decide the most appropriate algorithm based on the values passed to fit method

K-Nearest Neighbors: AKA lazy, instance-based learning

Lazy: No training process

Instance-based: Construct only local approximation to the target function that differs based on the neighborhood of each new query instance

Are there any disadvantages?

Cost of classifying new instances can be high:

- Nearly all computation takes place at classification time rather than learning time
- Number of points needed for good coverage of feature space scales exponentially with number of dimensions

What are some other ML methods?

Logistic Regression

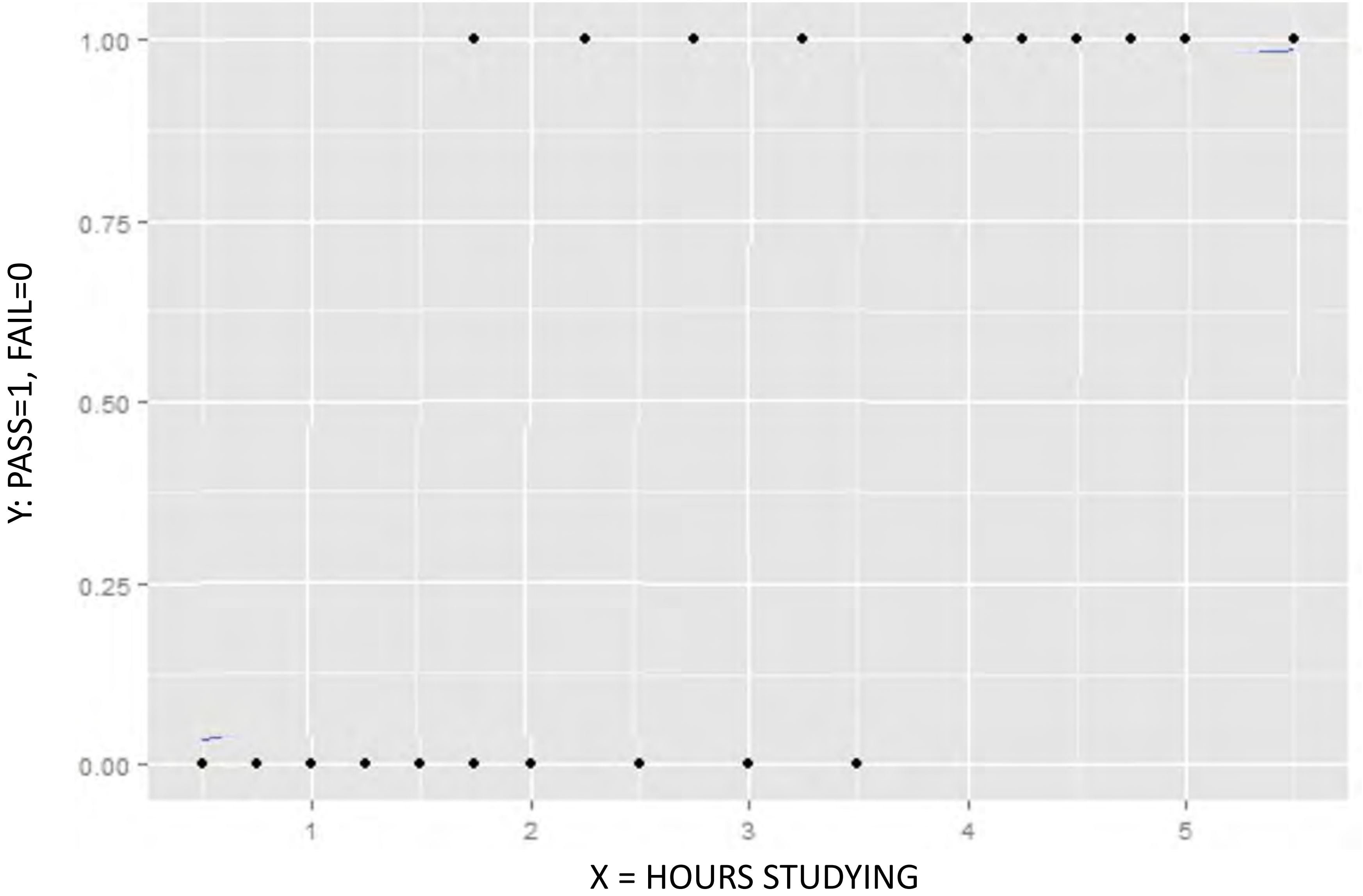
VERY simple example

HOURS STUDYING	PASSED EXAM
4	YES
1	NO
3.5	NO
2.25	YES
0.25	NO

Known input

Known labels

VERY simple example

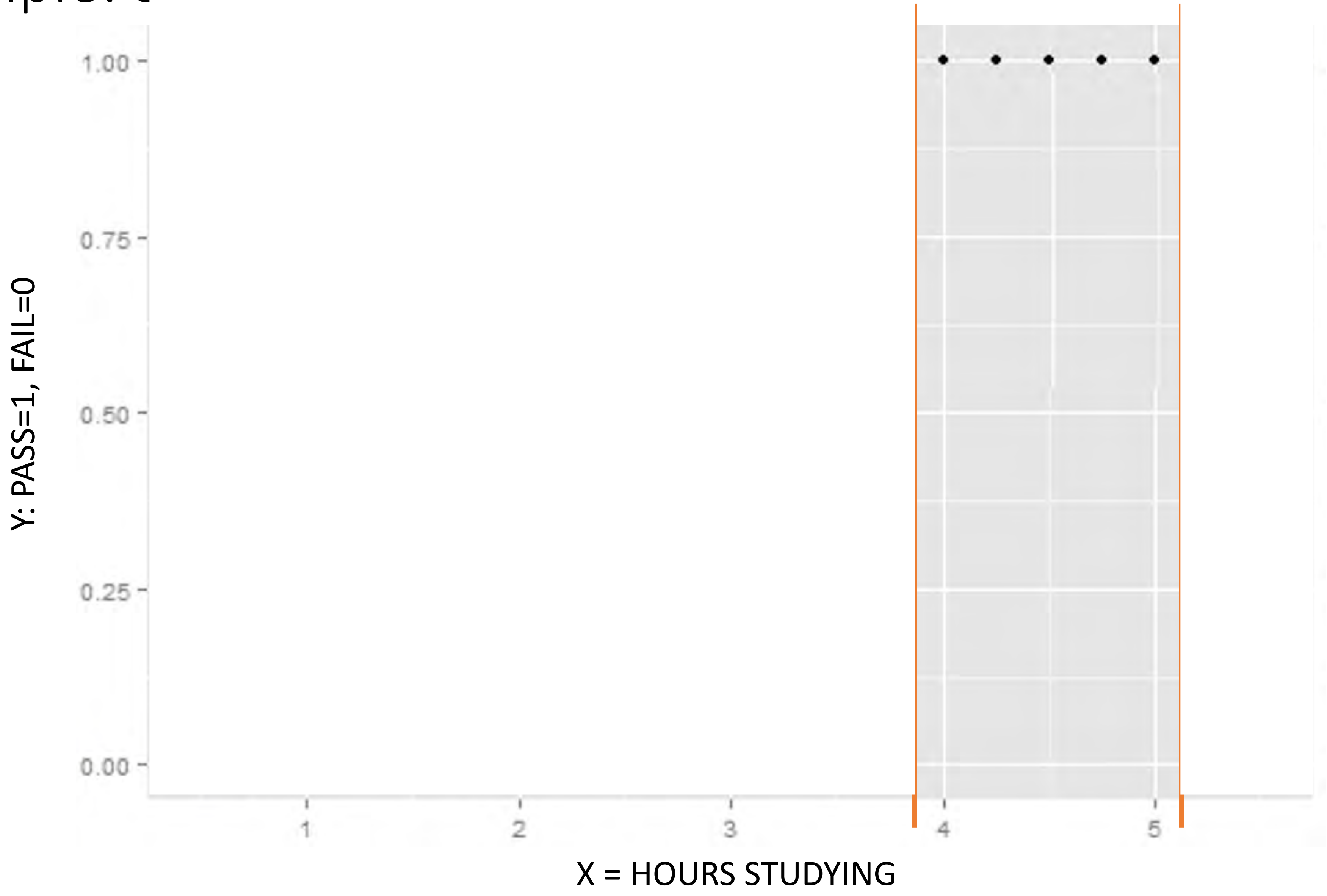


VERY simple example: 5

New point: X=4.5

All five neighbors
are labeled PASS

Predicted label = PASS



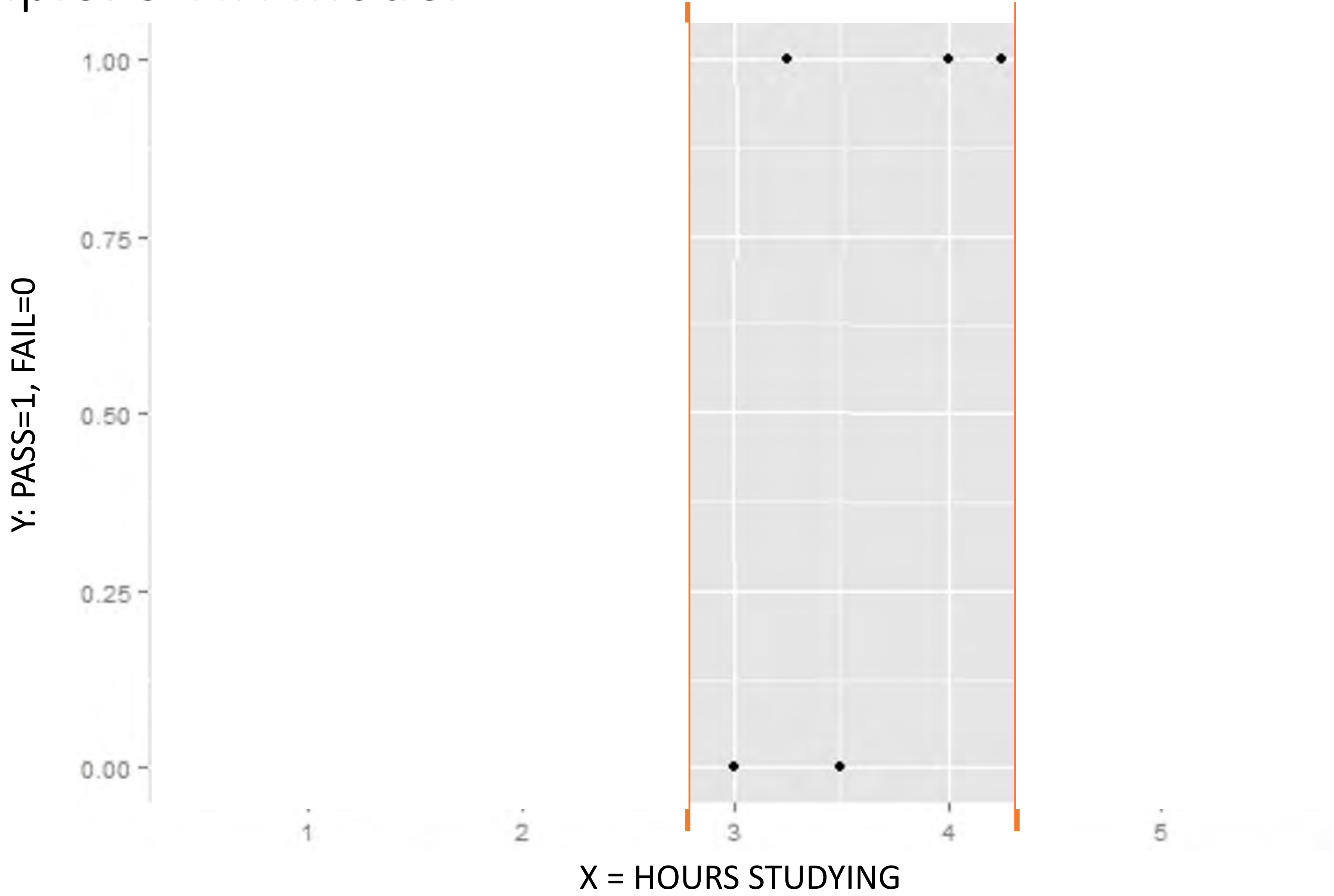
VERY simple example: 5-NN model

New point: X=3.5

three neighbors
are labeled PASS,
and two neighbors
are labeled FAIL

Predicted label = PASS

with probability 60%



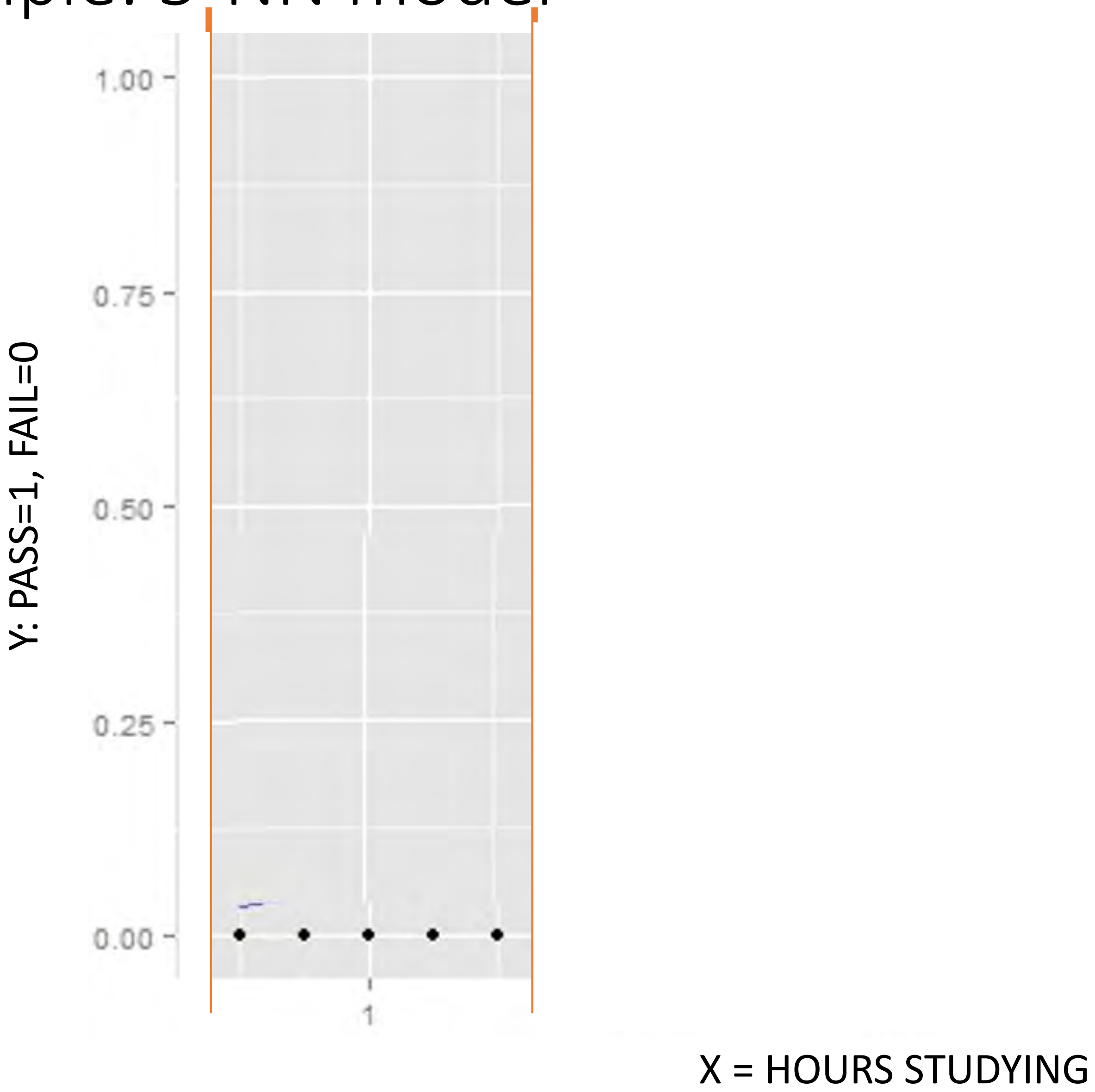
VERY simple example: 5-NN model

New point: X=1

All five neighbors
are labeled FAIL

Predicted label = PASS

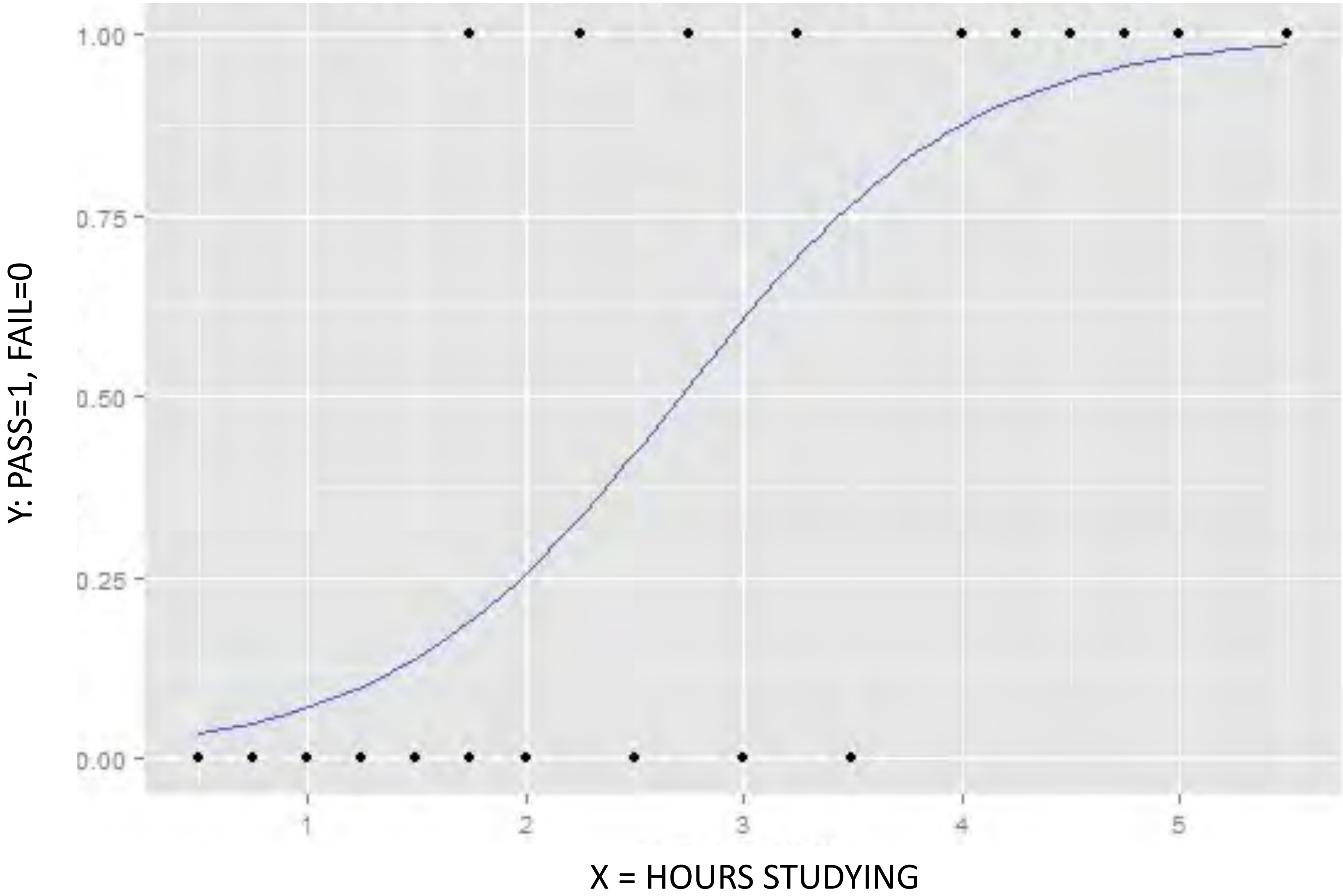
with probability 0%



VERY simple example

Blue line is

The probability of PASS being the correct label for a new point X



Prob(y) = Proportion of "success" among neighbors

$$Prob(y) = \frac{\sum y_i}{n} = \frac{\#\,\text{of}\ 1's}{\#\ \text{of trials}} = \text{Proportion of "success"}$$

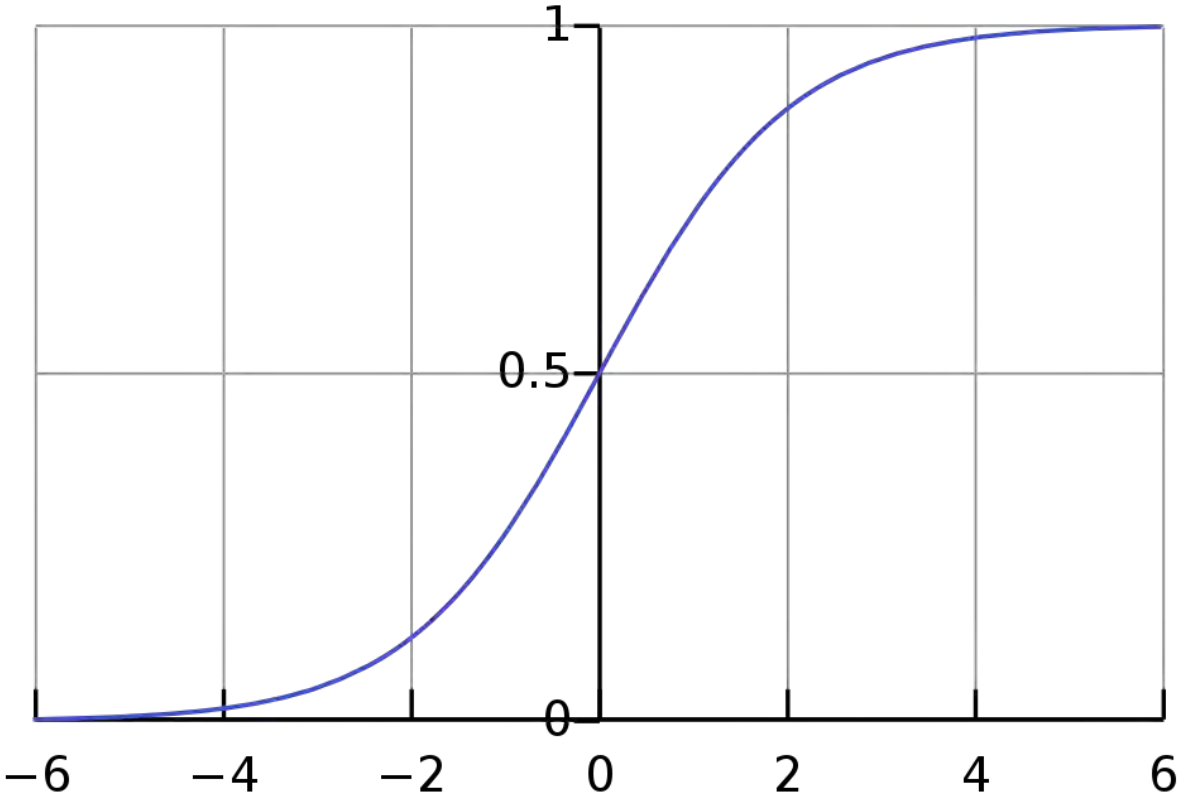
Goal of logistic regression: Predict the "true" proportion of success prob(y) at any value of the predictor variable X

Approximated by maximizing conditional log-likelihood: $\sum$ log *prob*(y|x)

Model for Prob(y)

The logistic function

$$\text{Probability(y)} = \frac{1}{1+e^{-x}} = \frac{e^x}{e^x+1}$$

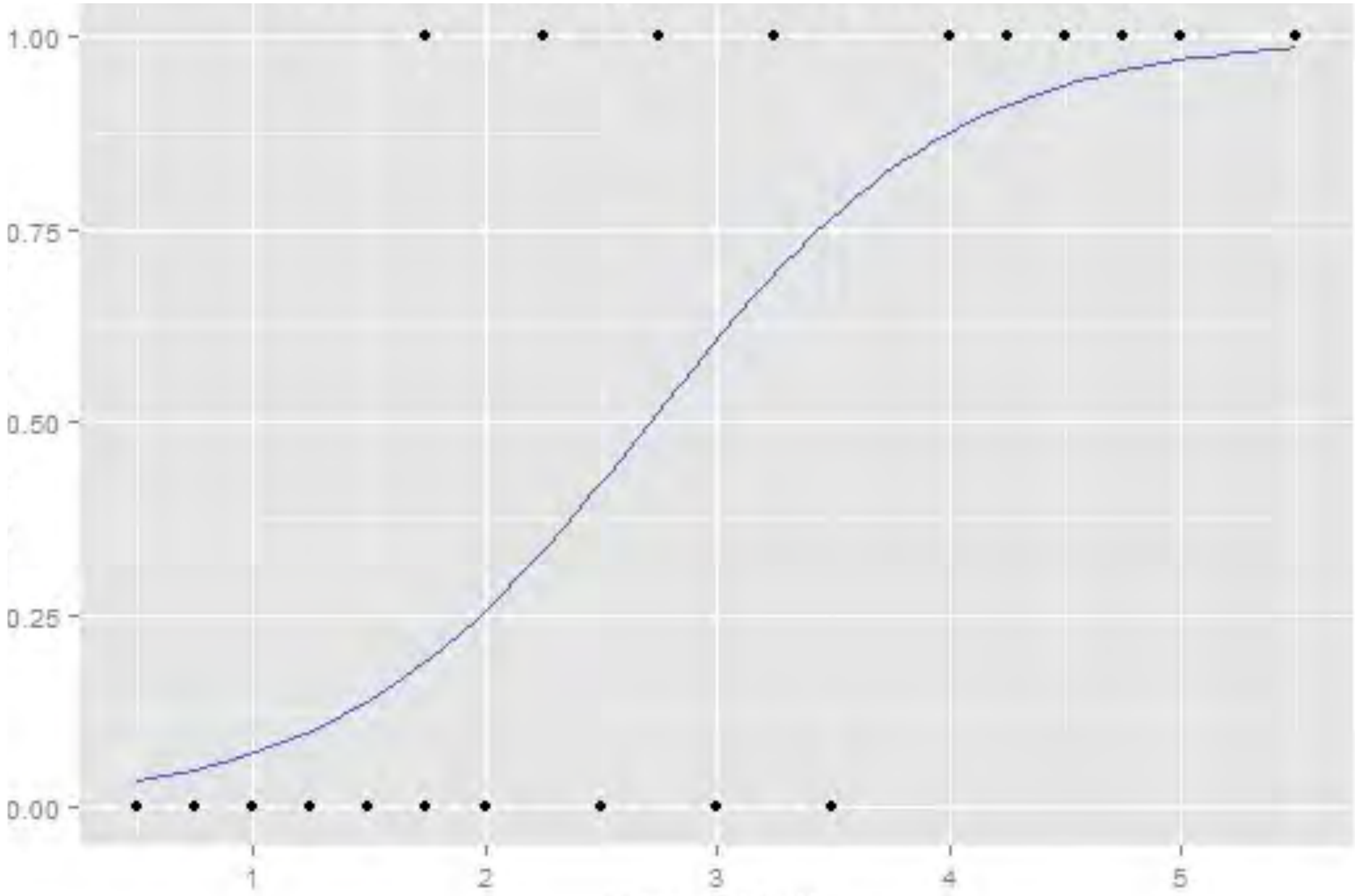


X axis

VERY simple example

Probability(PASS) =

$$\frac{1}{1+\exp(-(1.5046 \cdot \text{Hours} - 4.0777))}$$



X = HOURS STUDYING

In practical terms

HOURS STUDYING	PASSED EXAM
4	YES
1	NO
3.5	NO
2.25	YES
0.25	NO

Known input

Known labels

Replace

with

HOURS STUDYING	PROB. PASS
4	%
1	%
3.5	%
2.25	%
0.25	%

Compute formula based on logistic function

The logistic function in more dimensions

$$Probability(Y) = \frac{e^{u}}{1+e^{u}} = \frac{1}{1+e^{-u}}$$

Where u is the regular linear regression equation on M variables:

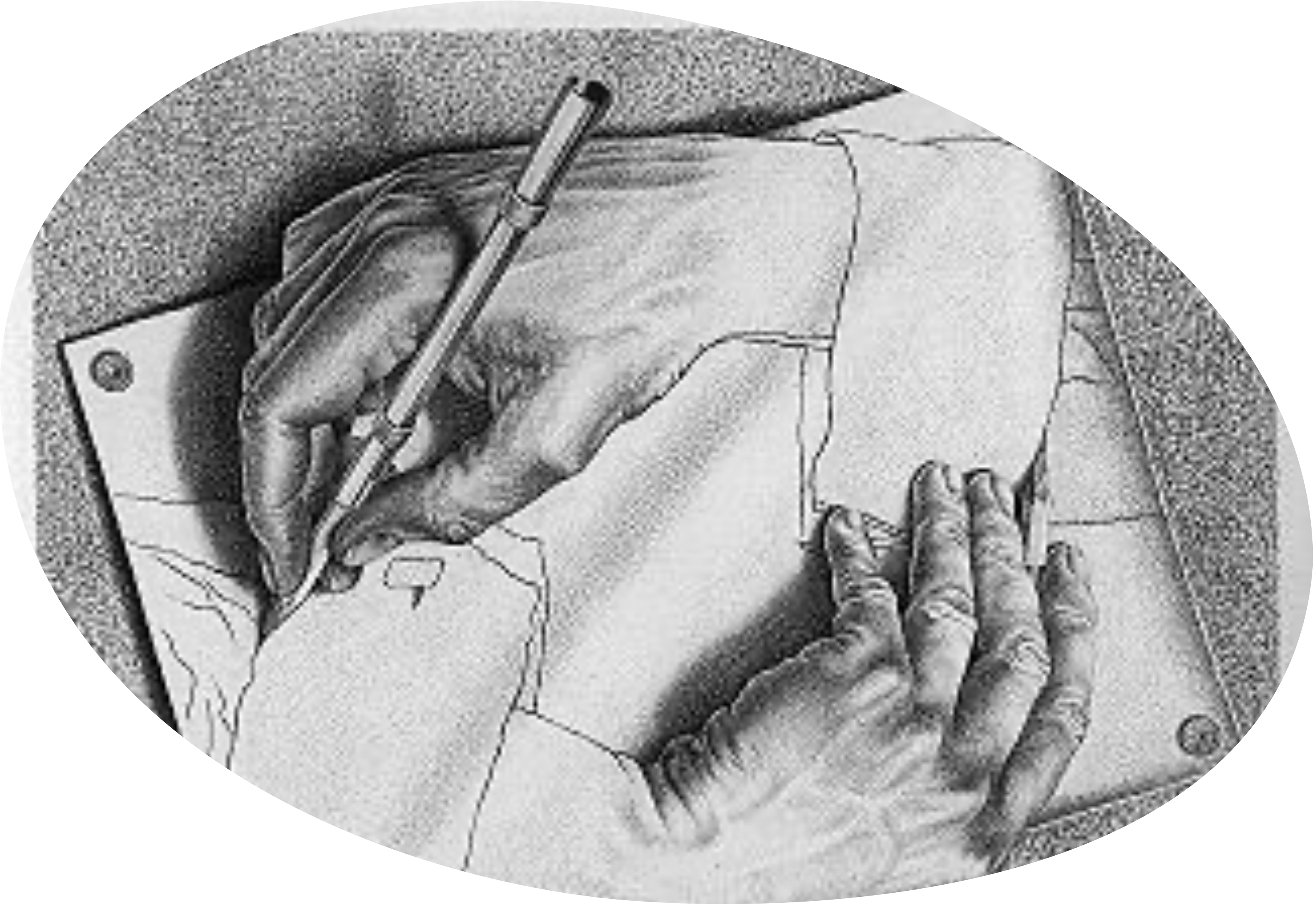
$$u = A + B_1 X_1 + B_2 X_2 + \ldots + B_M X_M$$

Logistic Regression

Form of regression that allows the prediction of discrete variables by a mix of continuous and discrete predictors

Addresses the same questions that multiple regression does, but requires no distributional assumptions on the predictors:

- do not have to be normally distributed
- do not have to be linearly related
- do not have to have equal variance in each group



Hands-on Example:

Logistic regression

Logistic Regression Classifier

LogisticRegression(*penalty='l2'*,
dual=False,
tol=0.0001,
C=1.0,
fit_intercept=True,
intercept_scaling=1,
class_weight=None,
random_state=None,
solver='lbfgs',
max_iter=100,
multi_class='auto',
verbose=0,
warm_start=False,
n_jobs=None,
l1_ratio=None)

https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LogisticRegression.html

Measuring how closely the formula fits the data

- **Penalty** {‘l1’, ‘l2’, ‘elasticnet’, ‘none’}, default=’l2’ Used to specify the norm used in the penalization. If ‘none’ (not supported by the liblinear solver), no regularization is applied.

- **C** float, default=1.0 Inverse of regularization strength; must be a positive float. Smaller values specify stronger regularization.

- **l1_ratio** float, default=None The Elastic-Net mixing parameter, with 0 <= l1_ratio <= 1. Only used if penalty='elasticnet'. Setting l1_ratio=0 is equivalent to using penalty='l2', while setting l1_ratio=1 is equivalent to using penalty='l1'. For 0 < l1_ratio <1, the penalty is a combination of L1 and L2

Choosing a method for solving the fitting problem

- **solver**{‘newton-cg’, ‘lbfgs’, ‘liblinear’, ‘sag’, ‘saga’}, default=’lbfgs’ Algorithm to use in the optimization problem. Not every solver choice will work with every penalty choice.
- **max_iter** int, default=100 Maximum number of iterations taken for the solvers to converge.