Overview

This is the "trailer" for the course: a brief plot summary and introduction to the key characters you will encounter.

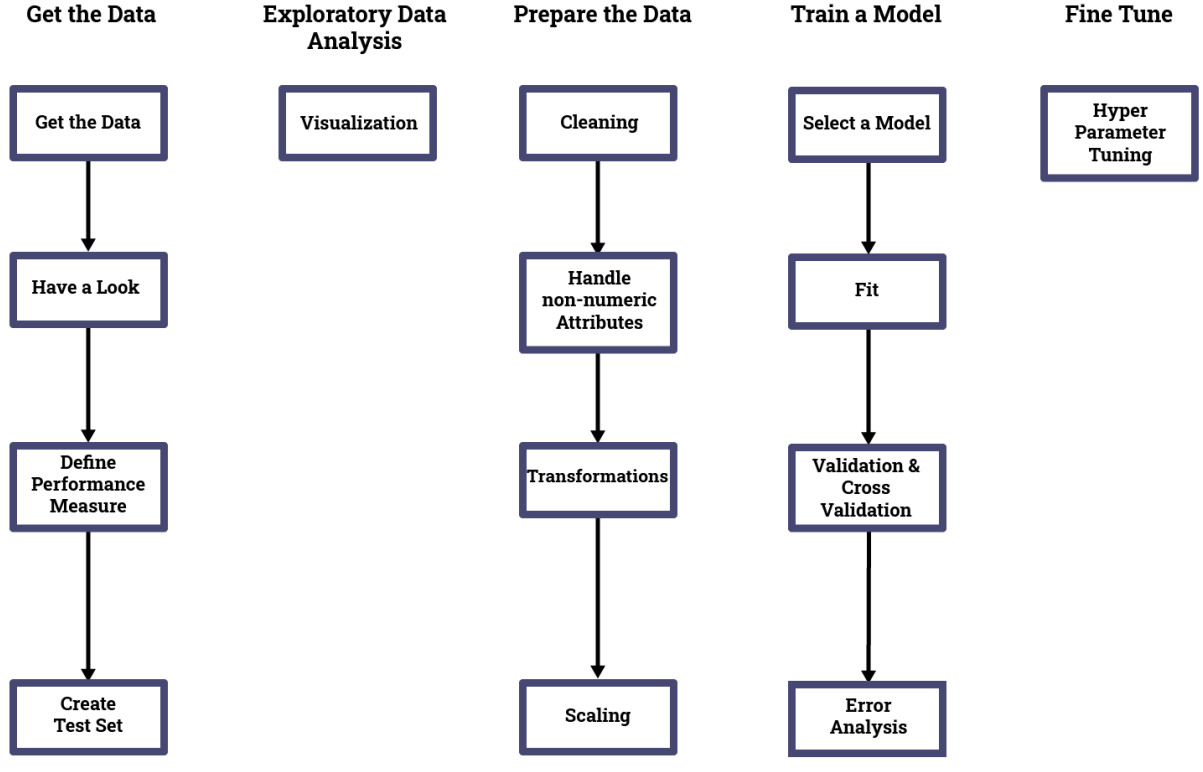
Goals

- Get a high level view of Machine Learning
- Introduce notation
- Preview concepts

Process for Machine Learning

Our belief is that Machine Learning should be taught as a *process* for problem solving.

The following picture will be our agenda; each column is one step in the process.


Get the Data
Get the Data
Have a Look
Define Performance Measure
Create Test Set
Exploratory Data Analysis
Visualization
Prepare the Data
Cleaning
Handle non-numeric Attributes
Transformations
Scaling
Train a Model
Select a Model
Fit
Validation & Cross Validation
Error Analysis
Fine Tune
Hyper Parameter Tuning

In contrast, many approaches focus on a few steps under "Train a model"

- Select a model
- Fit

At two extremes, these approaches either focus on "using an API" or deep math.

This may lead to the ability to construct models but, in our opinion, what distinguishes an adequate Data Scientist from a good one are all the other steps in the process.

To be sure, this course will both teach you how to use an API for Machine Learning and contain a fair amount of math.

But we take an engineer/scientist approach and focus on insight and repeatability (hence, process)

- we view Data Science as an experimental science
- your experiments are implemented via code
- you need to understand enough math to diagnose problems and improve experiments

So *expect to do a lot of coding*.

- You don't need to be a "professional" programmer
- But you do need to be a *disciplined* programmer to ease repeatability
    - Subprograms/classes (methods) versus cut and paste

Also expect some math

- in order to understand why a model is appropriate or not, and to diagnose why it is not working
- **not** to be able to derive formulae

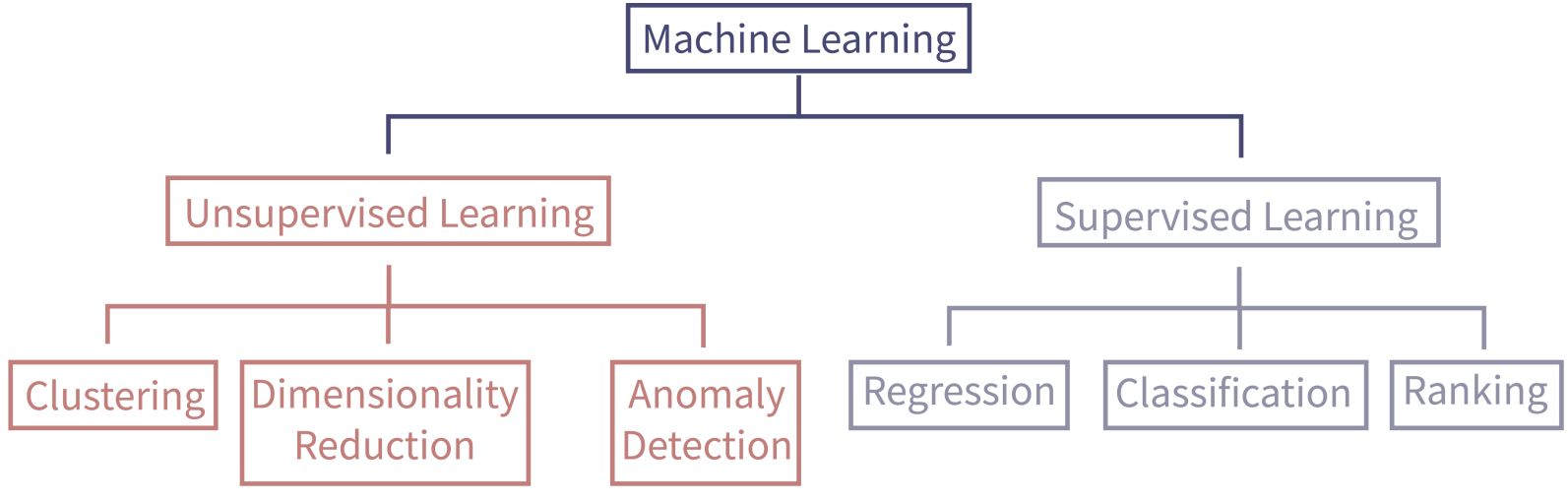
Classical ML and Deep Learning

There are two main streams in this course

- "Classical ML"
    - somewhat long history
    - somewhat related to Statistics
- "Deep Learning"
    - really took off after 2010
    - more related to Artificial Intelligence than Statistics
        - experimental versus mathematical

This preview is for Classical Machine Learning.

The big picture



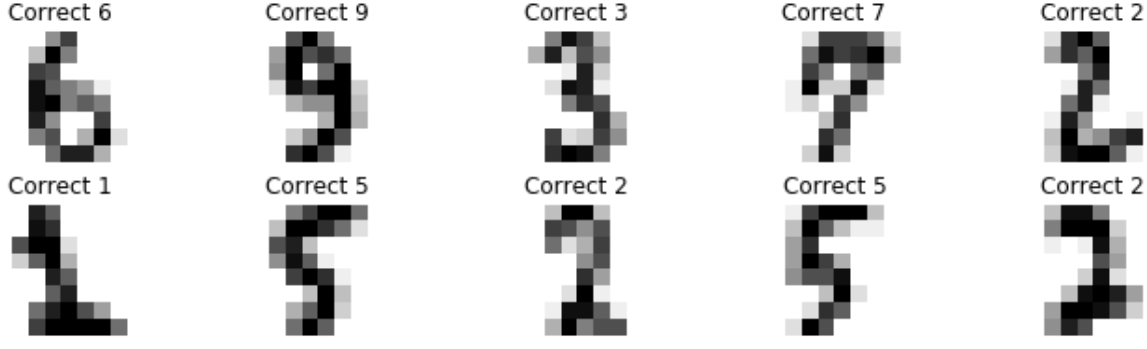
Supervised Learning

Supervised learning is about *informed prediction*.

Let's parse these word

- prediction
- informed

Prediction: what digits do these pixels represent ?



Prediction: Given an image that we haven't seem before, determine which digit it represents.

More formally:

- A single input $\mathbf{x}$ is a vector of length n, i.e., a collection of n *features*.
- A **predictor** is a map from $\mathbf{x}$ to a class (label) $\hat{\mathbf{y}}$.

The previously unseen image: $\mathbf{x}$ consists of $n = 64$ pixels (arranged as an 8×8 grid.

$\hat{\mathbf{y}}$ is the digit that we will say the image represents.

For now:

- a class is drawn from a finite set C of potential classes.
- we are describing Classification -- mapping $\mathbf{x}$ to a single class.
- we will extend to Regression: outputs are from a continous universe (e.g., numbers)

An example is a pair $(\mathbf{x}, c)$ of a feature vector $\mathbf{x}$ and a class $c \in C$ (the target).

Informed prediction is when the probability of the predictor making a correct prediction is greater than $\frac{1}{||C||}$.

- Consider a single example $(\mathbf{x}, c)$.
- A simple but naive predictor would map $\mathbf{x}$ to a random $c' \in C$.

The probability of the predictor being correct ($c' = c$) is $\frac{1}{||C||}$.

How do we achieve this ?

Supervised Learning makes the prediction based on having seen multiple, correctly labelled examples.

- It tries to *generalize*: find some pattern in the examples that is associated with the label.
- Perhaps the individual features (elements of $\mathbf{x}$) are associated with the correct class c.
- The aim of Supervised Learning is to create a function (predictor) that maps an $\mathbf{x}$ to the correct c.

Notation

Let's review our Notational standards (ML_Notation.ipynb)

Fundamental assumption of Machine Learning

Our goal is to learn (from training examples) to make a good prediction on a never before seen *test* example.

A necessary condition is that the training examples are representative of the future test examples we will encounter.

Let's imagine that there is some true (but unknown) distribution p_{data} of feature/label pairs $(\mathbf{x}, \mathbf{y})$.

In order to learn, we must assume

- That each test example $(\mathbf{x}, \mathbf{y})$ is drawn from p_{data}
- The *training examples* are a sample drawn from p_{data}.

We sometimes call the training data an *empirical* distribution -- it is just a sample, not the "true" distribution.

That is: our model can only generalize based on training examples

- The training examples need to be representative of unseen examples in the wild in order to generalize well
- Larger training sets are preferred as they may be more representative of the true p_{data}
    - They should also be diverse

If the test example $\mathbf{x}$ is not from p_{data}, the model is unconstrained in its prediction.

Making it concrete: Let’s predict !

Let's load a dataset to make these concepts concrete

In [5]:

```
import class_helper
%aimport class_helper

clh= class_helper.Classification_Helper()
X_digits,  y_digits = clh.load_digits()
```

- Let's see what m (number of examples), n (number of features) are

In [6]:

```
import numpy as np

print("m={m:d} training examples".format(m=X_digits.shape[0]))
print("n={m:d} features per example".format(m=X_digits.shape[1]))
targets = np.unique(y_digits)
targets.sort()

print("{nc:d} classes: {c:s}".format(nc=len(targets), c=", ".join( [ str(t) for
t in targets ]) ) )
```

```
m=1797 training examples
n=64 features per example
10 classes: 0, 1, 2, 3, 4, 5, 6, 7, 8, 9
```

In [7]:

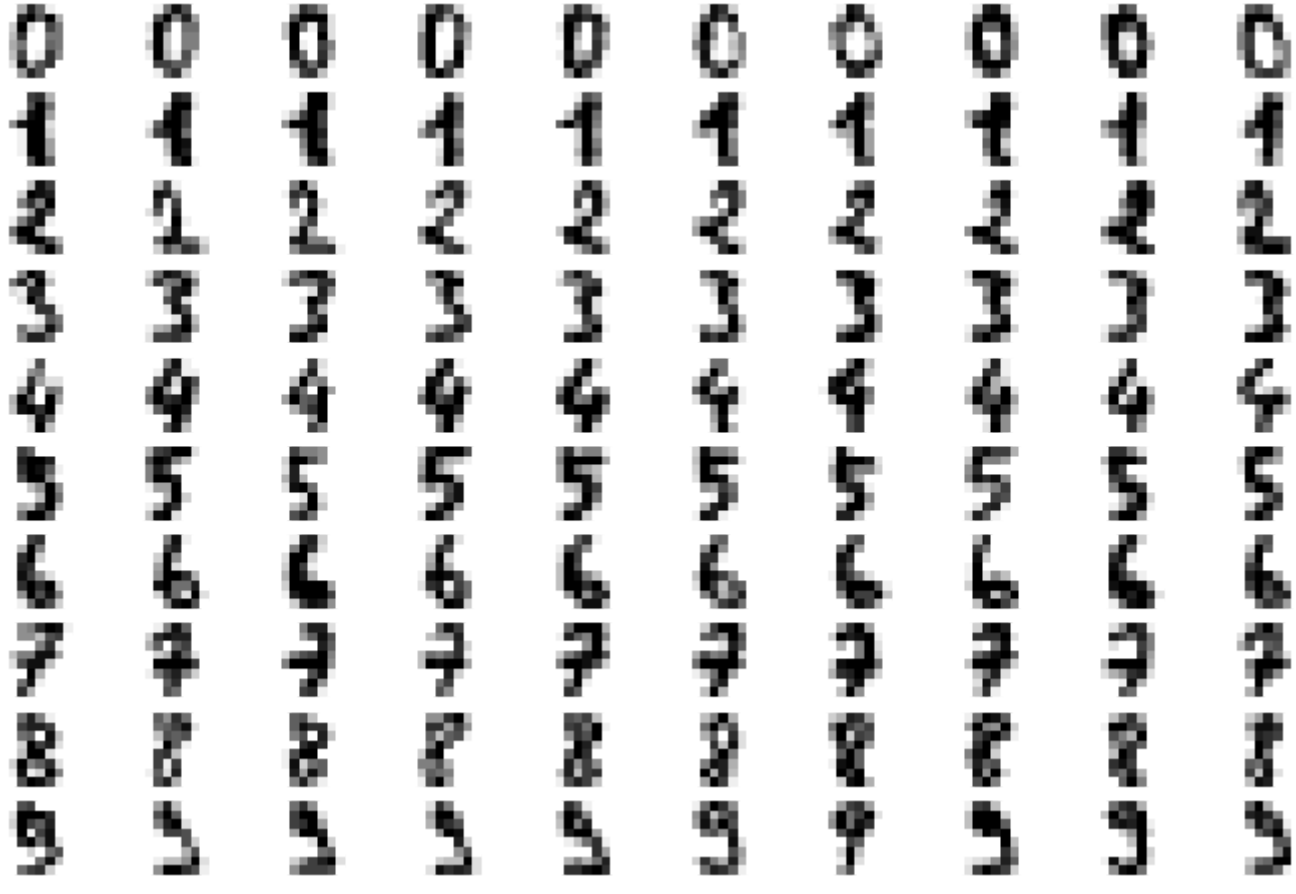
```
# Across the features of all examples: what is the min and the max ?
# Let's look at the feature vector for example at index ex_num
ex_num = 0
print("\nExample {n:d}, range({mn:2.2f}, {mx:2.2f}):\n\t ".format(n=ex_num,
                                                                  mn=X_digits.min(),
mx=X_digits.max()
                                                                 ),
      X_digits[ex_num,:]
     )
```

```
Example 0, range(0.00, 1.00):
          [0.     0.     0.3125 0.8125 0.5625 0.0625 0.     0.     0.     0.
 0.8125 0.9375 0.625  0.9375 0.3125 0.     0.     0.1875 0.9375 0.125
 0.     0.6875 0.5    0.     0.     0.25   0.75   0.     0.     0.5
 0.5    0.     0.     0.3125 0.5    0.     0.     0.5625 0.5    0.
 0.     0.25   0.6875 0.     0.0625 0.75   0.4375 0.     0.     0.125
 0.875  0.3125 0.625  0.75   0.     0.     0.     0.     0.375  0.8125
 0.625  0.     0.     0.    ]
```

- The dataset contains a number of examples.
    - Each example $\mathbf{x^{(i)}}$ is a vector of 64 features, which are numbers in the range $[0, 1]$
    - The target $y^{(\mathbf{i})}$ is a digit in the range $[0, 9]$
- In other words: the examples are encodings of images with labels that indicate what the image is.

Since the examples are grey scale values, we can re-arrange them into a square grid and plot:

In [8]:
```
fig, axs = clh.plot_digits(X_digits,  y_digits)
```

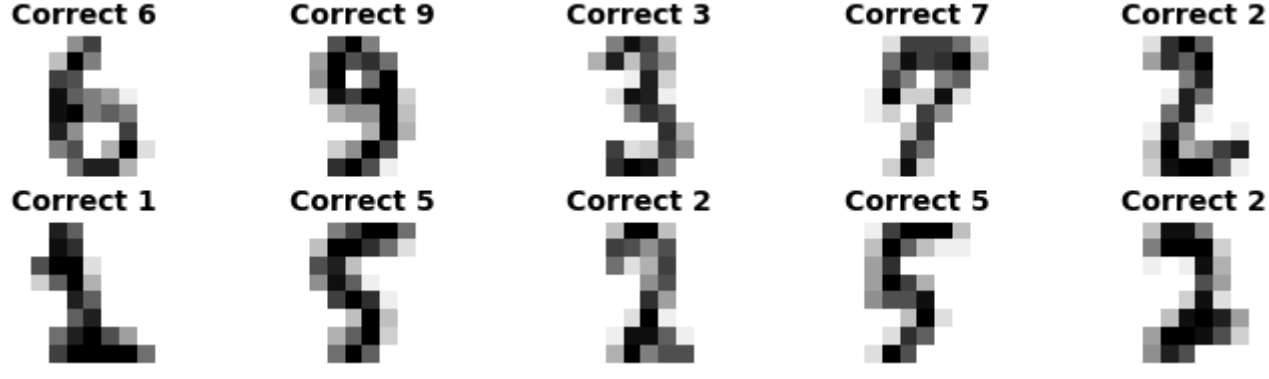


- Our problem is to take an unknown $\mathbf{x}$ and map it (predict) to a label in the range $[0, 9]$.
- This is a *classification* problem as our predictions are from a finite set.

In [9]:
```
Xd_train, Xd_test, yd_train, yd_test, models = clh.fit_digits(X_digits, y_digits
)

_= clh.predict_digits(models["knn"], Xd_test[:10], yd_test[:10])
```

```
KNN score: 0.990000
LogisticRegression score: 1.000000
```



- How would **you** predict a label for an image, given the 64 pixel values ?
- We will use a very simple (and inefficient) algorithm called *K Nearest Neighbors (KNN)*.

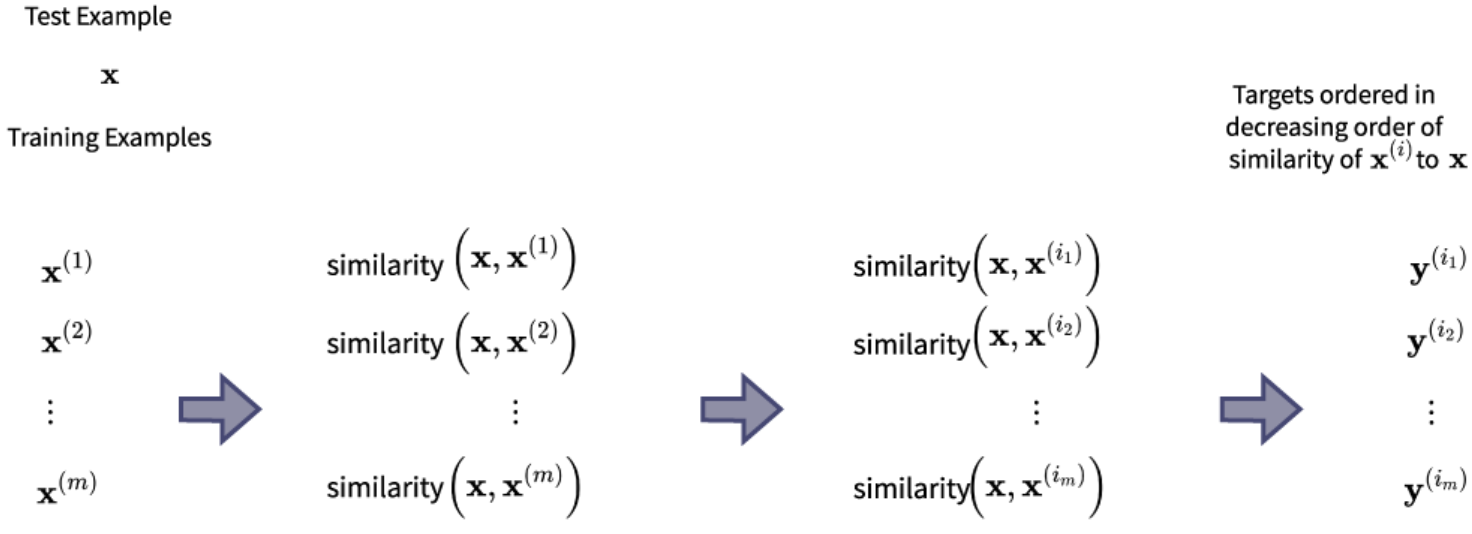
Template matching

- One approach to Classification is to match our input vector $\mathbf{x}$ against a *template*: (a vector of similar length) whose class is known.
- With one template $\mathbf{v}_{(c)}$ for each class $\mathbf{c} \in C$, we could classify $\mathbf{x}$ as being in the class c' whose template was "closest" to $\mathbf{x}$.
- We need a similarity measure that maps $\mathbf{x}$ and $\mathbf{v}_{(c)}$ to a number such that larger means more similar.

Our first predictor: K Nearest Neighbors (KNN)

- Here's one of the simplest Machine Learning algorithms, that leverages template matching.
- In this case, the templates are the feature vectors of the training set.
- Use the similarity measure to find the K training examples closest to $\mathbf{x}$;
- Predict the class that appears most frequently among these K examples.

- Here is our predictor function, given *test* input $\mathbf{x}$:
    - For each training example $\mathbf{x^{(i)}}$, compute the similarity $s^{(\mathbf{i})}$ of $\mathbf{x}$ to $\mathbf{x^{(i)}}$
    - Let S_K be the set of K training examples $i_1, i_2, \ldots, i_K$ with greatest similarity to $\mathbf{x}$
        - $Y = [\mathbf{y}^{(j)} | \; j \in S_K]$ be the classes associated with these closest examples
    - Let count_c be the number of elements of Y that are equal to class $c, c \in C$.
    - Predict class c', with the greatest $\mathrm{count}_{c'}$



Prediction: $\hat{\mathbf{y}}$ = most frequently $\left(\mathbf{y}^{(i_1)}, \ldots, \mathbf{y}^{(i_k)}\right)$

Here's an illustration of KNN in action:

- training example
  $$\mathbf{x^{(i)}} = [\mathbf{x}_1, \mathbf{x}_2], \mathbf{y^{(i)}} \in \{0, 1\}$$
  is plotted as a colored dot, with the color corresponding to $\mathbf{y^{(i)}}$
- we form many test (non-training) examples by creating arbitrary pairs of $\mathbf{x}_1, \mathbf{x}_2$ values in a grid
  - predict for each, fill the grid with a color corresponding to the predicted class

The line separating colors (classes) is called the *separating* or *decision* boundary.

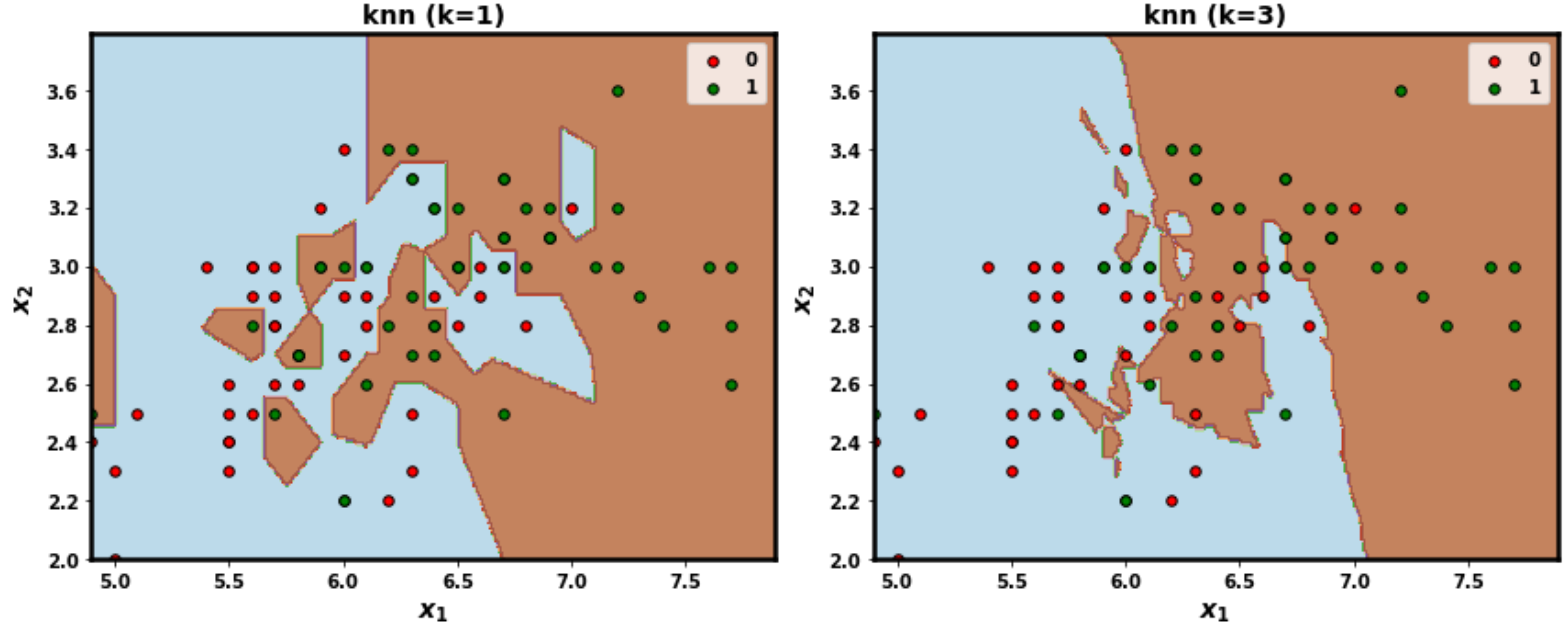
In [10]:

```
from sklearn.neighbors import KNeighborsClassifier

classifiers =  [ ("knn (k=1)", KNeighborsClassifier(1)),
                 ("knn (k=3)", KNeighborsClassifier(5))
               ]
svmh = svm_helper.SVM_Helper()
_= svmh.create_kernel_data(classifiers=classifiers)
fig, axs = svmh.plot_kernel_vs_transform(show_margins=False)
plt.close()
```

In [11]:
```
fig
```

Out[11]:



- KNN operates under the assumption (Manifold Hypothesis) that if two vectors are similar, they have the same class.
- If $K = 1$, the predictions are highly sensitive to the training examples; increasing K may increase the prediction accuracy.

Although simple, can you spot the drawback to KNN ?

$\Theta = \mathbf{X}$

- The size of Θ (the number of parameters) is proportional to
    - the size of the training set: $m * n$
    - ideally: m is very large, so Θ is big

Note

- *Always* count the number of parameters (size of Θ)
- You may be surprised how many you are estimating in comparsion to the amount of training data

KNN is so simple it's almost embarassing to call it Machine Learning. But it does illustrate the key steps

- the basis of Supervised Learning are training examples
    - the more the better
- the training examples are used to *fit* a predictor
    - we will learn many predictors (models) in this course
- the features of the examples are the key to prediction

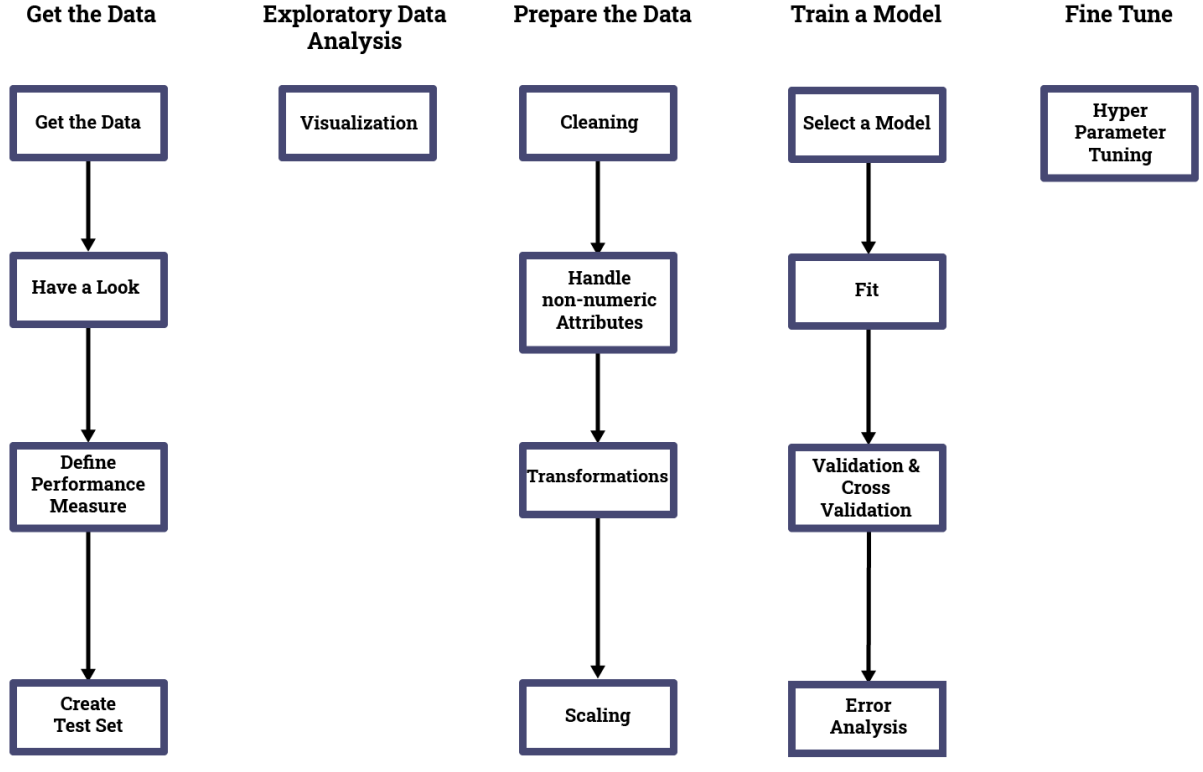
- KNN did not make intelligent use of the features: it merely memorized the m examples.
    - That is, it used m templates each of size n so $\left|\Theta\right| = m * n$.
- We will see that many ML algorithms, both Classic (e.g., Regression) and Deep Learning, are based on *solving* for Θ -- finding small templates that are effective for prediction.
- A more intelligent basis for prediction would include:
    - finding one (or more) features that are predictive
    - finding relationships among features that are predictive
    - find a subset of features that is *common across all examples* in a class.

- Another issue: perhaps we are using the wrong features ?
    - are $n = 64$ raw pixels the best representation of the input (and template) for learning ?
    - would higher level features (e.g., groups of pixels that form horizontal/vertical lines) be more efficient ?
- This is called Data Transformation or Feature Engineering and will be key concept.

Summary

- Machine Learning is a *process* that involves multiple steps
    - It is *not* just learning to use various models (predictors)
    - We will emphasize the process as much as the algorithms
- Supervised Machine Learning depends on the availability of data
    - obtaining, cleaning, augmenting data is important
- An example is a collection of "features"
    - finding/creating/interpretting features is the key skill of a Data Scientist
        - which features are important
        - how do features interact
    - sometimes features are missing or too low level
    - a key skill is creating features than enable learning ML

- A key part of Machine Learning is stating an optimization objective that captures your goal
    - not always obvious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Fit
Validation & Cross Validation
Error Analysis
Fine Tune
Hyper Parameter Tuning

In [12]:
```
print("Done")
```

```
Done
```