

# Becoming a successful Data Scientist: Error Analysis

As of now, you should know

- how to construct models (the "recipe")
- how to use them for prediction
- some simple metrics on how they perform

In this module, the topics to be covered provide answers:

- model diagnostics

In other words: the importance of Error Analysis in diagnosing and improving models.

# **Classification: Beyond accuracy**

Let's re-run the MNIST problem and examine measures of error more detailed than accuracy

```
In [5]: mnh = mnist_helper.MNIST_Helper(random_seed=42)
        mnh.setup()
        _ = mnh.fit()
```

Retrieving MNIST\_784 from cache

Examine the score (n.b., ran with L2 penalty)

```
In [6]: clf = mnh.clf

        # Cross validation
        scores = cross_val_score(clf, mnh.X_train, mnh.y_train, cv=10)
        print("Avg cross val score={s:3.2f}\n".format( s=scores.mean())) )

        # How many zero coefficients were forced by the penalty ?
        sparsity = np.mean(clf.coef_ == 0) * 100

        print("Sparsity with {p} penalty: {s:.2f}.".format(p=clf.penalty, s=sparsity) )
```

Avg cross val score=0.87

Sparsity with l2 penalty: 16.07.

We achieved an out of sample accuracy of about 87%

That sounds good, but is it really ?

If each of the 10 labels occurs with equal frequency among the training examples

- We could mis-predict *every* occurrence of a single digit (i.e., 10% of the training examples)
- And still achieve an Accuracy of 90% if we perfectly predict all other digits

Would that be satisfactory ?

This motivates the need to measure *Conditional Performance* or *Conditional Loss*

- Performance/Loss conditioned on meaningful subsets of training examples

We will examine some conditional metrics for the Classification task.



# Binary classification: Conditional accuracy

An ideal model would have perfect Accuracy.

In the absence of perfection

- we want to measure accuracy *conditional* on subsets of examples.

For a Binary Classification task, we can partition the examples into a two dimensions

- Row labels: the *predicted* class
- Column labels: the *true* class

	<b>P</b>	<b>N</b>
<b>P</b>	TP	FP
<b>N</b>	FN	TN

### The correct predictions

- True Positives (TP) are examples predicted as Positive that were in fact Positive
- True Negatives (TN) are examples predicted as Negative that were in fact Negative

### The incorrect predictions

- False Positives (FP) are examples predicted as Positive that were in fact Negative
- False Negatives (FN) are examples predicted as Negative that were in fact Positive

Unconditional Accuracy can thus be written as

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}}$$

We can also define some conditional Accuracy measures

# Imbalanced data: the case for conditional accuracy

Conditional Accuracy becomes particularly important

- when the number of Positive and Negative examples in a dataset are quite different
  - Titanic example: many fewer examples with Survived than Not Survived

This is called *imbalanced* data.

When this occurs, unconditional measures are highly influenced by success on the dominant category

- Titanic example: The Negative examples are almost twice as numerous as the Positive

$$TP + FN \ll TN + FP$$

Conditional metrics are one way of placing focus on success in the non-dominant category.

## Recall (Sensitivity, True Positive Rate: TPR)

Regardless of whether the Positive class is dominant, we may be interested in how well our model identifies Positive examples.

*Recall* is a metric Conditioned on Positive examples.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

- The fraction of Positive examples (denominator) that were correctly classified
- Also goes by the names: True Positive Rate (TPR), Sensitivity

**FN** (mis-classified Positive examples) detract from Recall

Why is Recall important ?

Consider a diagnostic test for Covid

- we want to correctly identify Covid positive patients
- even though they are a small fraction of the population



But be careful ! It is easy to achieve 100% Recall.

Degenerate case:

- Always predicting Positive, ignoring all features of the example
  - lots of FP
- Unconditional Accuracy will suffer.
- And FP (Negative patients incorrectly classified as infected) may bear a cost

# Specificity

Similarly: we may be interested in knowing how well our model identifies (or mis-identifies) Negative examples.

For example

- we *don't want to mis-label* as Positive, a patient who is truly Covid Negative.

*Specificity* is a metric conditioned on Negative examples

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}}$$

- The fraction of Negative examples that were correctly classified
- Also goes by the name: True Negative Rate (TNR)

**FP** (mis-classified Negative examples) detract from Specificity

A good model (e.g., Covid test) has

- high Recall
  - correctly identifies a large fraction of Positive patients
- high Specificity
  - does not have too many FP (mis-diagnosed Negative patients)
    - who may bear a cost of being mis-diagnosed

## False Positive Rate (FPR)

The fraction of Negative examples misclassified as Positive.

$$\begin{aligned}\text{FPR} &= \frac{\text{FP}}{\text{FP} + \text{TN}} \\ &= 1 - \text{Specificity}\end{aligned}$$

# Precision

Recall seeks to correctly label Positive examples

- degenerate case: label all examples as Positive; achieve 100% Recall

But we would also like to have confidence that our Positive predictions are accurate.

*Precision* is a metric to tell you the fraction of your Positive predictions that were correct.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

**FP** (mis-classified Negative examples) detract from Precision.

Just like with Recall, it is easy to achieve 100% Precision.

Degenerate case:

- Predict Positive for only a *single example* that is actually Positive
  - Lots of FN
  - Recall will suffer

# Precision/Recall Tradeoff

We showed (via degenerate cases) that it was easy to have **either**

- Perfect Recall
- **OR** Perfect Precision

But it may not be possible to have both.

We will

- Show how to trade off one measure for the other
- Discuss when to favor one type of error over another

Some Classification models (e.g., Logistic Regression)

- Use hyper-parameters (e.g., threshold)
- To convert a numerical "score" to a Categorical predicted value

By varying the threshold, we can change predictions to favor a particular Conditional Performance metric.

We will show how this happens and demonstrate ways to evaluate the trade-off between metrics.



Recall our methodology for Classification via Logistic Regression:

- Compute a numerical "score" for our example based on its features

$$\hat{s}^{(i)} = \Theta \cdot \mathbf{x}^{(i)}$$

- Construct a probability distribution (over the target classes) from the scores

$$\hat{\mathbf{p}}^{(i)} = \sigma(\hat{s}^{(i)})$$

- Predict by comparing the probability to a threshold

$$\hat{\mathbf{y}}^{(i)} = \begin{cases} 0 & \text{if } \hat{\mathbf{p}}^{(i)} < 0.5 \quad \text{Negative} \\ 1 & \text{if } \hat{\mathbf{p}}^{(i)} \geq 0.5 \quad \text{Positive} \end{cases}$$

We can visualize the step of converting probabilities to predicted class by plotting lines (hyper-planes) of constant score/probability

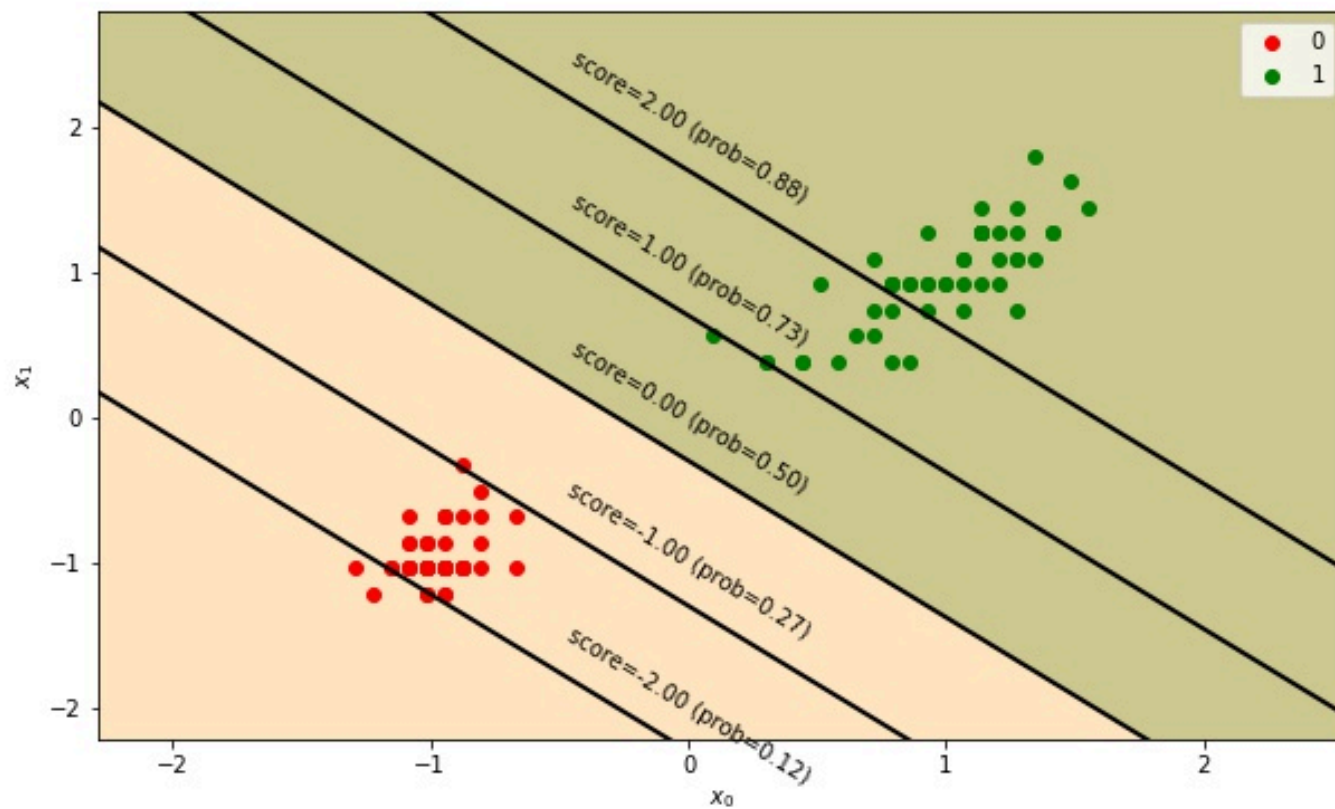
For a given constant value of score or probability:

- Examples above the line are classified as Positive
- Examples below the line are classified as Negative

We can choose **any score/probability** as our decision boundary for prediction.

Let's see what happens as we vary the boundary.

## Separation boundary as function of probability threshold



- By choosing the boundary  
 $\Theta^T \mathbf{x} = -1$  (resp., prob = 0.27)
- Rather than the boundary  
 $\Theta^T \mathbf{x} = 0$  (resp., prob = 0.50)

we potentially **increase** the number of examples classified as Positive

- Increasing the number of TP  $\rightsquigarrow$  Increasing Recall
- But also potentially increasing the number of FP  $\rightsquigarrow$  Decreasing Precision

Thus, by varying threshold, we can choose the **trade-off between Recall and Precision**.

For models that rely on a Threshold

- the threshold is a **hyper-parameter**
- that **you can choose**
- in order to achieve some externally-specified objective
  - e.g., high Recall

## **Precision vs Recall: which one to favor ?**

What factors might lead us to favor one metric over the other ?

Consider a diagnostic test whose goal is to classify highly infectious patients as Positive

- High Recall: catch most infected patients
- Low Precision: frighten patients that are misclassified as Positive

You might favor Recall

- When a False Negative has very bad consequences (e.g., lead to an increase in infections in population)

You might favor Precision

- When a False Positive has very bad consequences (e.g., cause a non-infected patient to isolate)

Moving the boundary to increase Positives will naturally decrease Negative predictions.

So we also affect metrics conditioned on Negative (FN, TN), with similar trade-offs.



## Precision/Recall trade-off: plot

To be concrete: let's examine the trade-off between Recall and Precision in the context of a binary classifier

- Using MNIST examples: classify an example as being a **single** chosen digit versus the 9 other digits
- Create a binary classifier for a single MNIST digit

```
In [7]: # Fetch the MNIST data into object

mnh_d = mnist_helper.MNIST_Helper(random_seed=42)
mnh_d.setup()

# Turn the 10 class training set into a binary training set
# - Same examples, different targets
# - targets are now "is 'digit'" or "is not 'digit'" for a single digit
digit = '5'
y_train_d, y_test_d = mnh_d.make_binary(digit)

# Fit a binary model: Is digit/Is not digit
mnh_d.fit(y_train=y_train_d)
scores = cross_val_score(mnh_d.clf, mnh_d.X_train, y_train_d, cv=3, scoring="accuracy")

from sklearn.model_selection import cross_val_predict

y_train_pred = cross_val_predict(mnh_d.clf, mnh_d.X_train, y_train_d, cv=5, method="decision_function")
```

Retrieving MNIST\_784 from cache

```
Out[7]: LogisticRegression(C=0.01, class_weight=None, dual=False, fit_intercept=True,
                           intercept_scaling=1, l1_ratio=None, max_iter=100,
                           multi_class='multinomial', n_jobs=None, penalty='l2',
                           random_state=None, solver='saga', tol=0.1, verbose=0,
                           warm_start=False)
```

Let's plot the trade-off

```

In [8]: from sklearn.metrics import precision_recall_curve

precisions, recalls, thresholds = precision_recall_curve(y_train_d, y_train_pre
d)

# Convert thresholds (log odds) to probability
probs = np.exp(thresholds)/(1+np.exp(thresholds))

def plot_precision_recall_vs_threshold(precisions, recalls, thresholds, probs=None):
    fig, ax = plt.subplots(1,1, figsize=(12,4))

    if probs is None:
        horiz = thresholds
        label = "Threshold"
    else:
        horiz = probs
        label = "Probability threshold"
    _ = ax.plot(horiz, precisions[:-1], "b--", label="Precision", linewidth=2)
    _ = ax.plot(horiz, recalls[:-1], "g-", label="Recall", linewidth=2)
    _ = ax.set_xlabel(label, fontsize=16)
    _ = ax.legend(loc="upper left", fontsize=16)
    _ = ax.set_ylim([0, 1])

    _ = ax.set_xlim([ horiz.min(), horiz.max()])

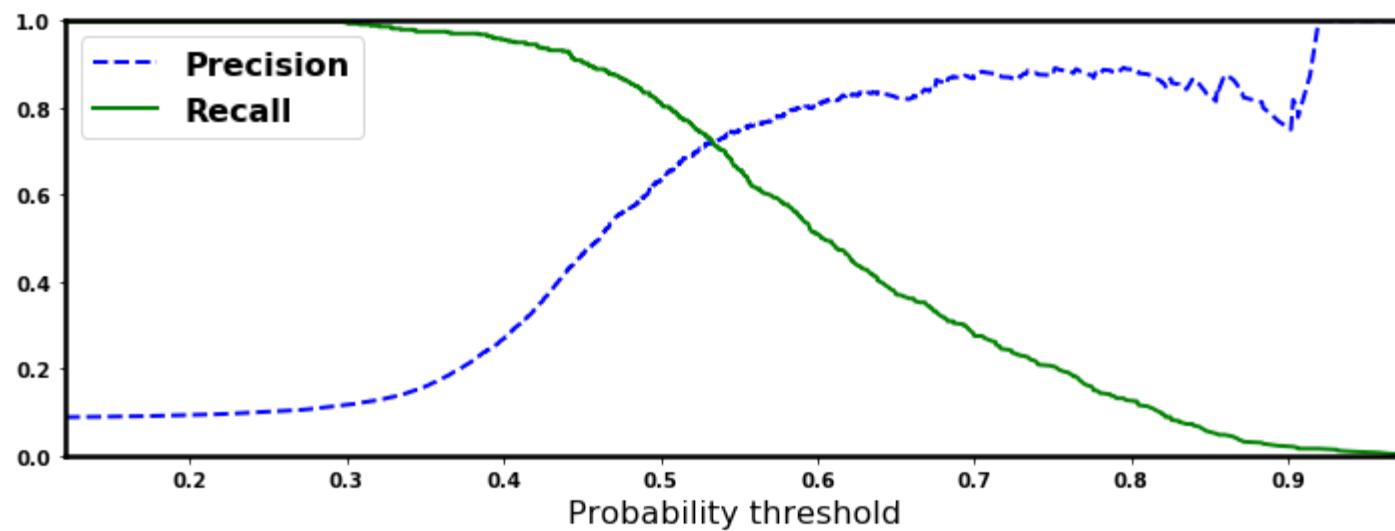
    return fig, ax

fig, ax = plot_precision_recall_vs_threshold(precisions, recalls, thresholds, pr
obs=probs)
plt.close(fig)

```

In [9]: fig

Out[9]:



You can see how varying the threshold affects Recall and Precision

- One at the expense of the other

## ROC/AUC: Evaluating the Precision/Recall tradeoff

There is another common tool used to evaluate the trade-off between competing metrics.

The **ROC** is a plot of True Positive Rate (TPR) versus the False Positive Rate (FPR) as we vary the threshold.

- each point in the plot corresponds to a particular threshold
- the TPR and FPR is measured for that threshold

Our goal is to choose a threshold (corresponding to a point on the curve)

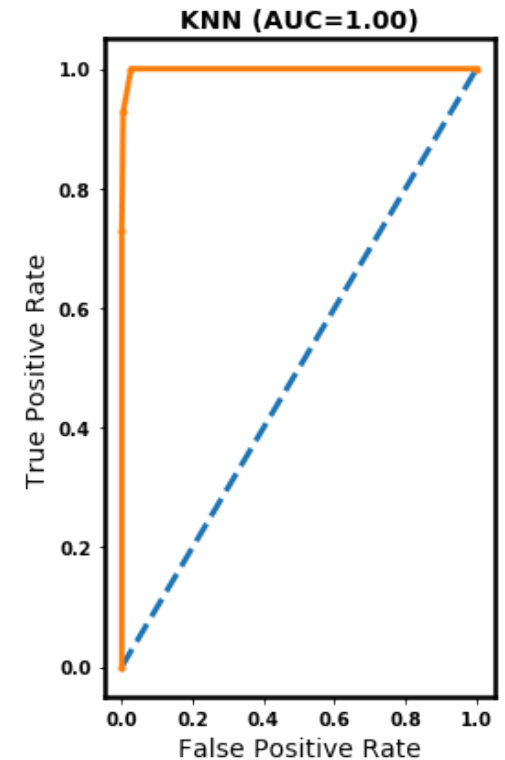
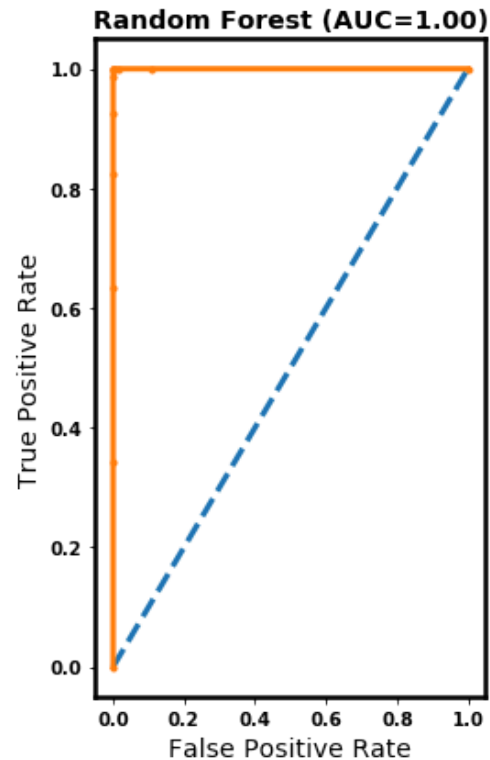
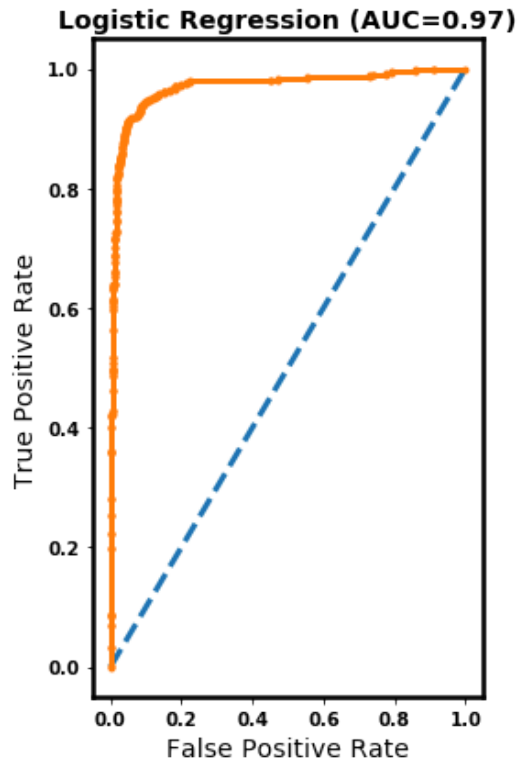
- With the highest True Positive Rate (TPR)
  - i.e., Recall
  - fraction of correctly classified Positives
- With the smallest *acceptable* False Positive Rate (FPR)
  - fraction of negatives that are misclassified as Positive
  - larger FPR means *worse* Precision



We illustrate by showing the ROC/AUC curve for three different classifiers on the MNIST digit recognition problem.

- Logistic Regression
- KNN
- Random Forests

```
In [10]: # ROC curves for binary classifier: Is Digit/Is not Digit  
clh.AUC_plot(X_train=mnh.X_train, y_train=y_train_d, X_test=mnh.X_train, y_test=  
y_train_d)
```



The "ideal" curve would resemble an inverted "L"

- With a top, horizontal line near a TPR of 1
- That rises vertically from a FPR of near 0

That would imply that there is a choice of threshold with low FPR and high TPR.

**You** decide which threshold produces an acceptable trade-off

But you can also compare the curves across models

- A model whose curve is closer to the inverted "L" shape has a better trade-off
- We can measure this by the *Area Under the Curve* (AUC) of the model
  - Higher AUC gets us closer to the ideal
- The model whose curve has highest AUC might be the model of choice.

## Note on the mechanics of plotting the ROC/AUC

To produce the ROC/AUC curve

- Fit a binary classifier
- For each possible value of the threshold
  - Predict using this threshold
  - Evaluate the TPR and FPR
  - This gives a single point on the curve

Fortunately: most ML toolkits will implement this process for you

- But the principle of "there is no magic" means that you should always understand what is happening

## **$F_1$ : Another way to combine Precision and Recall**

There another metric call the  $F_1$  which expresses the trade-off between Precision and Recall as a single number:

$$F_1 = \frac{TP}{TP + \frac{FN+FP}{2}}$$

# Multinomial classification: Confusion matrix

So far we have been dealing with a classifier with only two classes.

So the simple grid

	<b>P</b>	<b>N</b>
<b>P</b>	TP	FP
<b>N</b>	FN	TN

was sufficient.

The generalization of the grid to multiple classes is called the *Confusion Matrix*

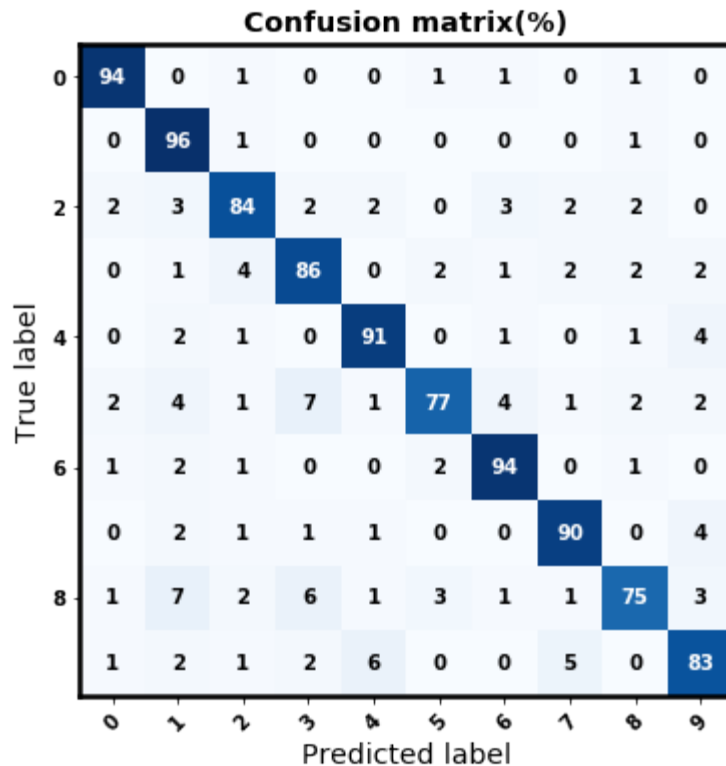
Here is the Confusion Matrix for a classifier on the task of predicting which of 10 digits is represented by an image (MNIST digit recognition)



```
In [11]: # Now predict the value of the digit on the second half:
fig, ax = plt.subplots(figsize=(12,6))
confusion_mat = mnh.create_confusion_matrix()

digits = range(0,10)
_ = clh.plot_confusion_matrix(confusion_mat, digits, ax=ax, normalize=True)
```

Normalized confusion matrix



- Column labels: the *predicted* class
- Row labels: the *true* class

The entry in the matrix for row  $i$ , column  $j$

- **Percentage** of examples for true digit  $i$  that were predicted as digit  $j$ .

The diagonal of the Confusion Matrix is the Recall for each digit/

The non-diagonal elements of a row show how often a given digit was mistaken for another.

The confusion matrix for MNIST digit recognition tells us that our classifier

- Does a great job (90+% correct) on images corresponding to digits 0,1,6
- Is struggling (< 80% correct) on images of the digits 5, 8
  - Mis-classifying them as "3" most often

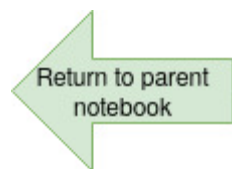
Studying the Confusion Matrix in depth can help you

- Diagnose the weaknesses in your model
- And *perhaps take steps to compensate* for them (improve the model)
- By analyzing the examples belonging to the subset corresponding to non-diagonal entries

**This is the true power of Error Analysis !**

- Having a process and the tools to diagnose mis-prediction will make you more successful !
- That is why we emphasize the importance of the Error Analysis step of the Recipe

We will perform this analysis *in code* for the MNIST digit classifier shortly.



## Regression: beyond RMSE/ $R^2$

What is the process of diagnosing errors for the Regression task ?

Answer: Examining the residuals.

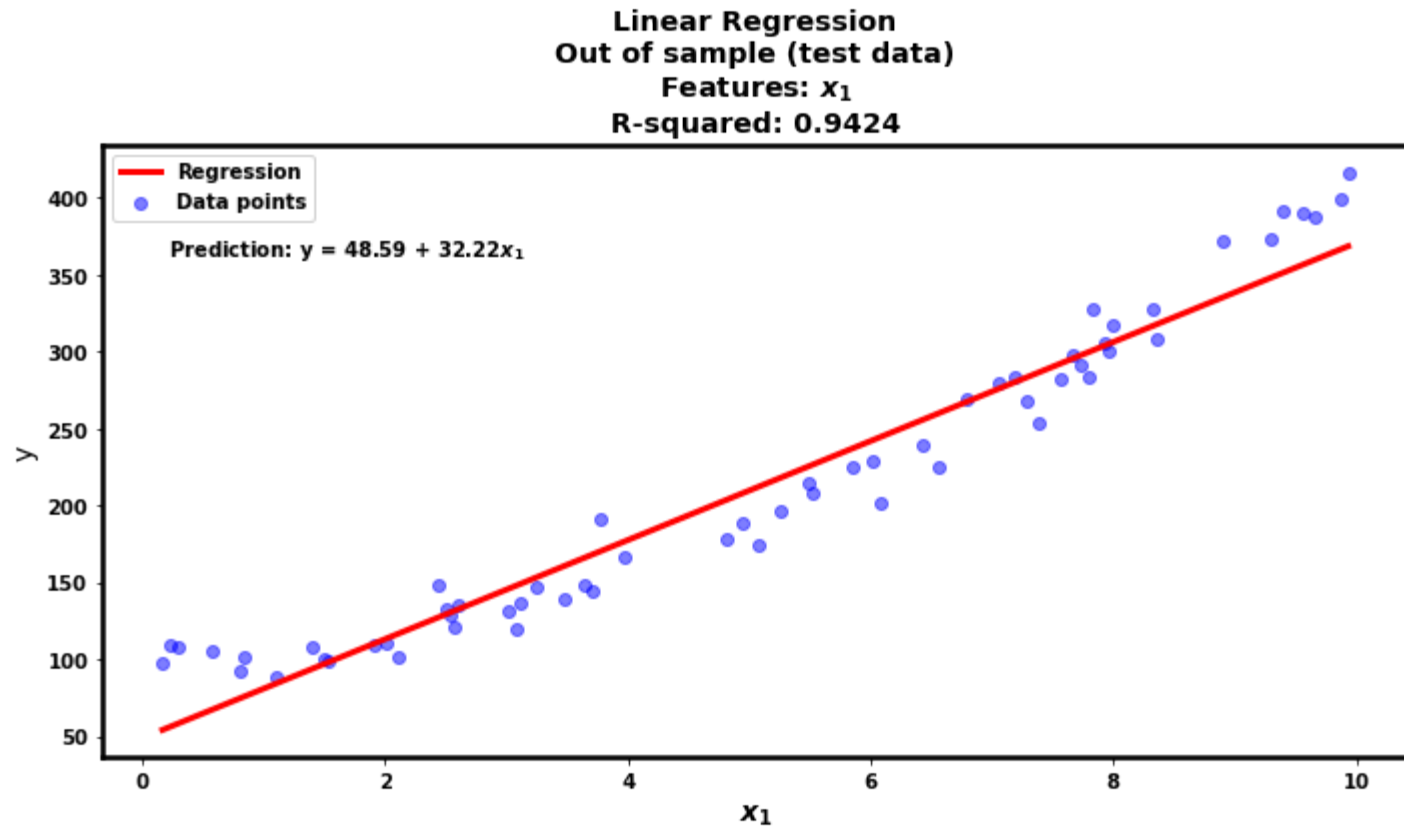
- the difference  $\mathbf{y}^{(i)} - \hat{\mathbf{y}}^{(i)}$

Recall our first attempt at Linear Regression

- where we systematically *under-predicted* (positive residuals) the Target
- for low and high values of the single feature  $\mathbf{x}_1$

In [14]: fig\_x1

Out[14]:





## Our Error Analysis

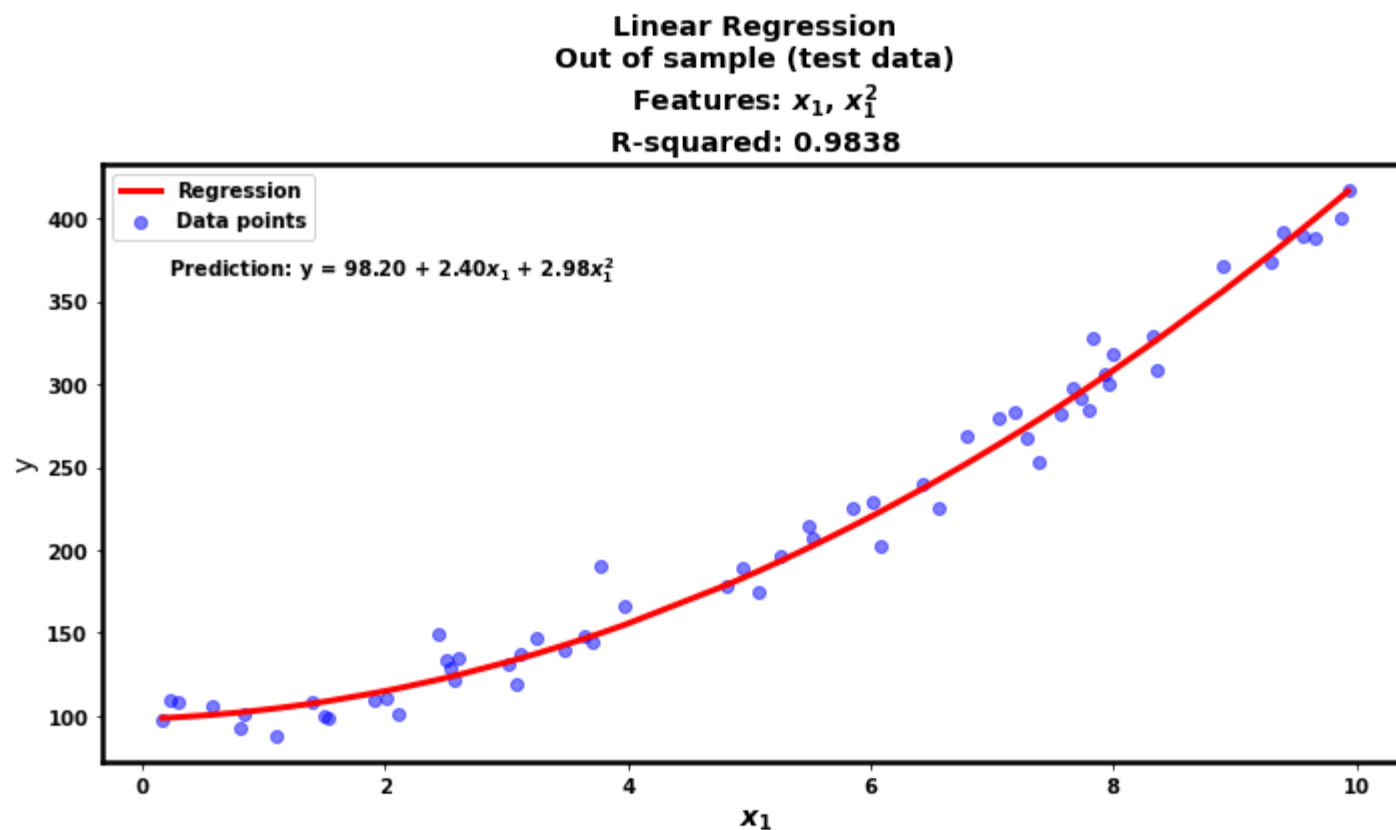
- observing the systematic mispricing

led us to improve the model

- by adding a second feature  $\mathbf{x}_1^2$

In [15]: fig\_x1\_x1sq

Out[15]:



```
In [16]: print("Done")
```

Done

