# Interpreting the coefficients in Linear Models

The dot product has been a recurring character during our Classical Machine Learning journey.

$$\Theta \cdot \mathbf{x}$$

By examining this expression more closely

- We can gain insight into what $\Theta$ means
- Understand mathematically why transformation may be necessary
- Gain an appreciation of the "pattern matching" that it embodies

Recall the places in which dot product appears

- Linear Regression
$$\hat{\mathbf{y}} = \Theta \cdot \mathbf{x}$$
- Logistic Regression
$$\hat{s} = \Theta \cdot \mathbf{x}$$
for score $\hat{s}$ (which becomes a probability via $\hat{p} = \sigma(\hat{s})$
- Boundary equation for linearly separable classifiers, e.g., SVM
$$0 = \Theta \cdot \mathbf{x}$$

Consider one feature $\mathbf{x}_j^{(\mathbf{i})}$ for example $i$.

- A unit increase in $\mathbf{x}_j^{(\mathbf{i})}$
- Holding constant the values for all other features,
- Increases $\Theta \cdot \mathbf{x}^{(\mathbf{i})}$ by $\Theta_j$

Thus

$$\Theta_j = \frac{\partial}{\partial \mathbf{x}_j} \Theta \cdot \mathbf{x}$$

$\Theta_j$ may be interpreted as

- The sensitivity of $\Theta \cdot \mathbf{x}$ to changes in feature $j$

# Numeric features

Consider numeric features $\mathbf{x}_j, \mathbf{x}_{j'}$.

Does

$$\Theta_j > \Theta_{j'}$$

mean that feature $j$ is "more important" than feature $j'$ ?

- No !
- It just means it has a larger impact
- Which can *also* occur if $\mathbf{x}_j, \mathbf{x}_{j'}$ are on different scales

For example consider the equality

$$\mathbf{y} = \Theta \cdot \mathbf{x}$$

- Replacing $\mathbf{x}_j$
- By $\mathbf{x}_{j''} = \mathbf{x}_j * 10$
- Mathematically results in $\Theta_{j''} = \Theta_j / 10$

Thus, the scale of the parameter is dependent on the scale of the feature.

Unless two features are on the same scale: we can't directly compare their corresponding parameters.

# Categorical features

Consider a categorical feature with categories from

$$C = \{c_1, c_2, \ldots\}$$

One Hot Encoding this feature replaces the original feature with $||C||$ binary features

- $\text{Is}_{c_1}$
- $\text{Is}_{c_2}$
- $\vdots$
- $\text{Is}_{c_{||C||}}$

Suppose $\mathbf{x}_j$ corresponds to the binary feature

$$\text{Is}_{c_1}$$

Then, by the formula for dot product

- $\Theta_j$ is the *increment* to $\Theta \cdot \mathbf{x}$
- Arising from $\mathbf{x}_j^{(\mathbf{i})} = 1$
- Compared to $\mathbf{x}_j^{(\mathbf{i})} = 0$

That is:

- $\Theta_j$ is how much $\Theta \cdot \mathbf{x}$ increases
- When example $i$ has feature value $c_1$ rather than any of $\{c_2, \ldots, \}$

We can use this interpretation

- To further emphasize the problem of
- Treating a categorical variables as a number rather than a collection of binary indicator variables

For example, let's revisit the Passenger Class `Pclass` $\in \{1, 2, 3\}$ from the Titanic example.

- As a collection of binary indicator variables, the increment of being in each class is $\Theta_{\mathrm{Is}_1}, \Theta_{\mathrm{Is}_2}, \Theta_{\mathrm{Is}_3}$
- As a numeric variable with parameter value $\Theta_j$
    - Being in Class 3 has three times the effect as being in Class 1

Thus

- As numeric, we imply a particular magnitude with each category
- As binary indicator,the magnitude is determined by the data

# Motivating a transformation

Understanding the meaning of $\Theta$ may help us choose a transformation.

Suppose we have examples $\langle \mathbf{X}, \mathbf{y} \rangle$ where

$$\mathbf{y} = \Theta \cdot \mathbf{x}$$

**does not** seem to hold.

Perhaps a transformation to either/both of $\mathbf{x}, \mathbf{y}$ **will** make the relationship linear.

For example, consider

- $\mathbf{y}$ and $\mathbf{x}$ are time-series of prices, with different scales
- We observe that the impact on $\mathbf{y}$ of a *unit change* in $\mathbf{x}_j$
    - Is much bigger when $\mathbf{x}_j$ is small
    - Compared to when $\mathbf{x}_j$ is large
- So

$$\mathbf{y} \neq \Theta \cdot \mathbf{x}$$

Now suppose we re-dominate (by transforming) the timeseries $\mathbf{y}$ and $\mathbf{x}$ to

- Timeseries $\mathbf{y}'$ $$= \text{daily } \% \text{ change in } \mathbf{y}$$
- Timeseries $\mathbf{x}'$ $$= \text{daily } \% \text{ change in } \mathbf{x}$$

This transformation from Price to Return is common in Finance.

It may now turn out that

- A unit change in $\mathbf{x}'$
- Results in a change in $\mathbf{y}'$
- That is *independent* of the magnitude of $\mathbf{x}'$
- So

$$\mathbf{y}' = \Theta' \cdot \mathbf{x}'$$

That is

- A $1$ percentage point change in the price of $\mathbf{x}$
- Causes $\mathbf{y}$ to change by $\Theta'$ percentage points

So there **was** a relationship between $\mathbf{y}$ and $\mathbf{x}$, not in Price but in Return.

The Capital Asset Pricing Model of Finance postulates such a relationship and it is common to transform prices to returns.

## Transformed targets

At times we may apply transformations to target values rather than just features.

This means that $\Theta_j$ is the sensitivity of the *transformed* target.

Recall that Logistic Regression could be formulated as

- Linear Regression of the features
- Versus the *log odds*

$$\log_e \frac{\hat{p}}{1-\hat{p}} = \mathbf{\Theta}^T \mathbf{x}$$

So a unit change in feature $\mathbf{x}_j$ with parameter $\Theta_j$ changes the *odds* $\frac{\hat{p}}{1-\hat{p}}$ in a *multiplicative* way

$$\log(\frac{\hat{p}}{1-\hat{p}}) + \Theta_j = \log\left(\frac{\hat{p}}{1-\hat{p}} * \exp\Theta_j\right)$$

-

# Examples

- Log transform of target:
  - $\log \mathbf{y} = \Theta_0 + \Theta_1 * \mathbf{x}_1$
  - $\theta_1 = \frac{\partial \log \mathbf{y}}{\partial \mathbf{x}_1} = \%$ change in $\mathbf{y}$ per unit change in $\mathbf{x}_1$
- Log transform of both target and feature:
  - $\log \mathbf{y} = \Theta_0 + \Theta_1 * \log \mathbf{x}_1$
  - $\Theta_1 = \frac{\partial \log \mathbf{y}}{\partial \log \mathbf{x}_1} = \%$ change in $\mathbf{y}$ per $\%$ change in $\mathbf{x}_1$
- Standardize feature
  - Transform $\mathbf{x}$ into $z_{\mathbf{x}} = \frac{\mathbf{x} - \bar{\mathbf{x}}}{\sigma_{\mathbf{x}}}$
  - $\mathbf{y} = \Theta_0 + \Theta_1 * z_{\mathbf{x}}$
  - $\Theta_1 = \frac{\partial \log \mathbf{y}}{\partial z_{\mathbf{x}}}$ change in $\mathbf{y}$ per $1$ standard deviation change in $\mathbf{x}$
    - since $z$ is in units of "number of standard deviations"

**Remember**

- if you transform features in training, you must apply the same transformation to features in test
  - if the transformation is parameterized, the parameters are determined at **train** fit time, not test !
- if you transform the target, the prediction is in different units than the original
  - you can perform the inverse transformation to get a prediction in original units

# Bucketing/Binning re-visited

Suppose $\mathbf{x}_j$ is a continuous numeric feature (e.g., `Age` ).

Some questions to consider

- Is a 1 year increase in age equally relevant for all ages ?
    - If so: numeric
- Is a 1 year increase in age of the same relevance for a senior adult compared to an infant ?
    - If not: consider reducing discrete ages to discrete buckets
    - Is there a linear relationship between target and the center point of the bucket ?
        - If so: bucket feature can be numeric
        - If not: bucket feature categorical

# Interpreting the MNIST classifier: template matching

The $\Theta$ produced by a linear classifier can be viewed as templates

- the strength of $\Theta_j$ tells you how strongly feature $\mathbf{x}_j$ influences the target

So we can interpret $\Theta$ as a "template" for what a model is looking for.

Let's look at the template for

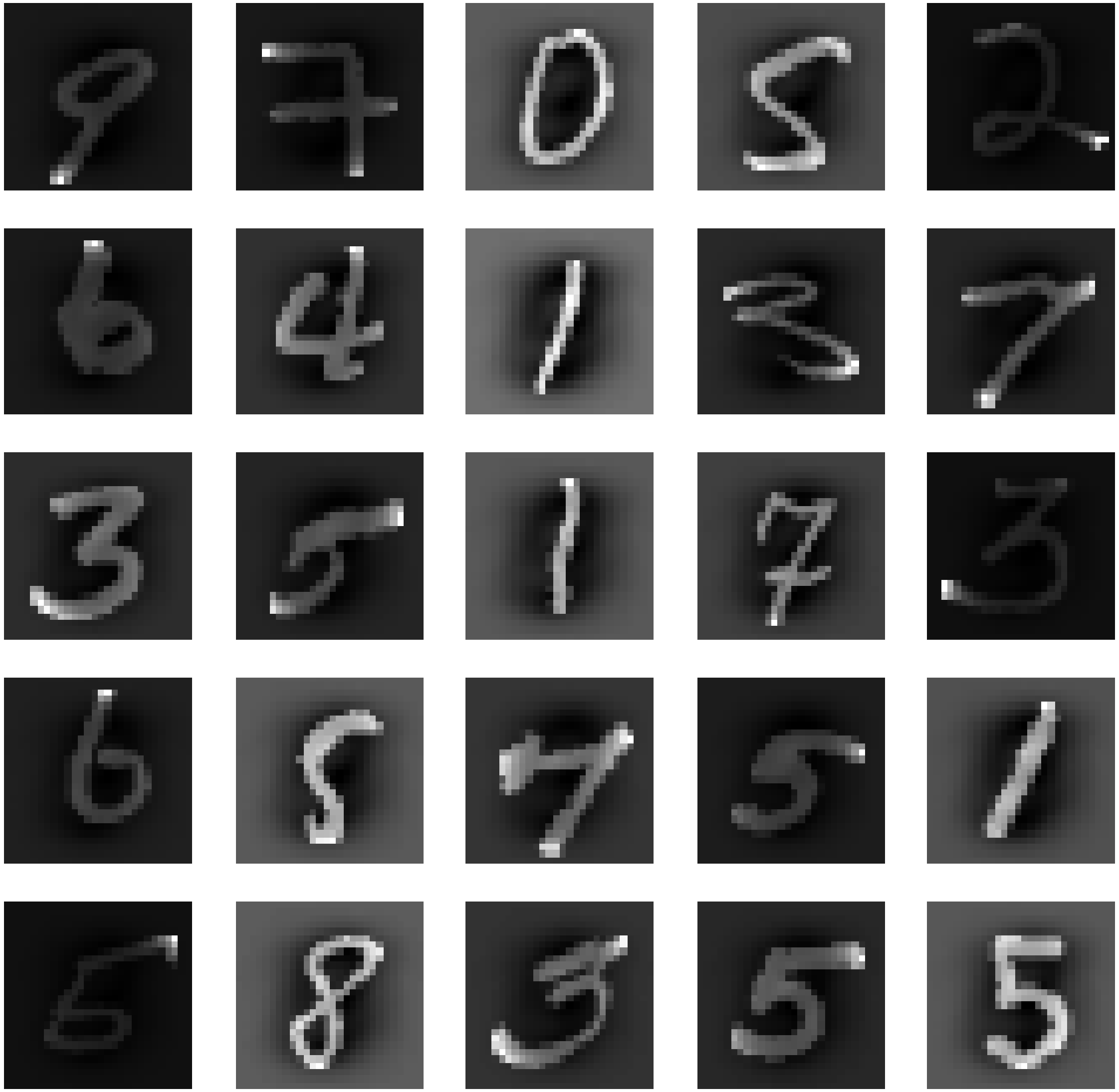
- The 10 separate, single-digit binary MNIST classifiers
- Or similarly: each *row* of $\Theta$ for the multinomial 10 class MNIST classifier

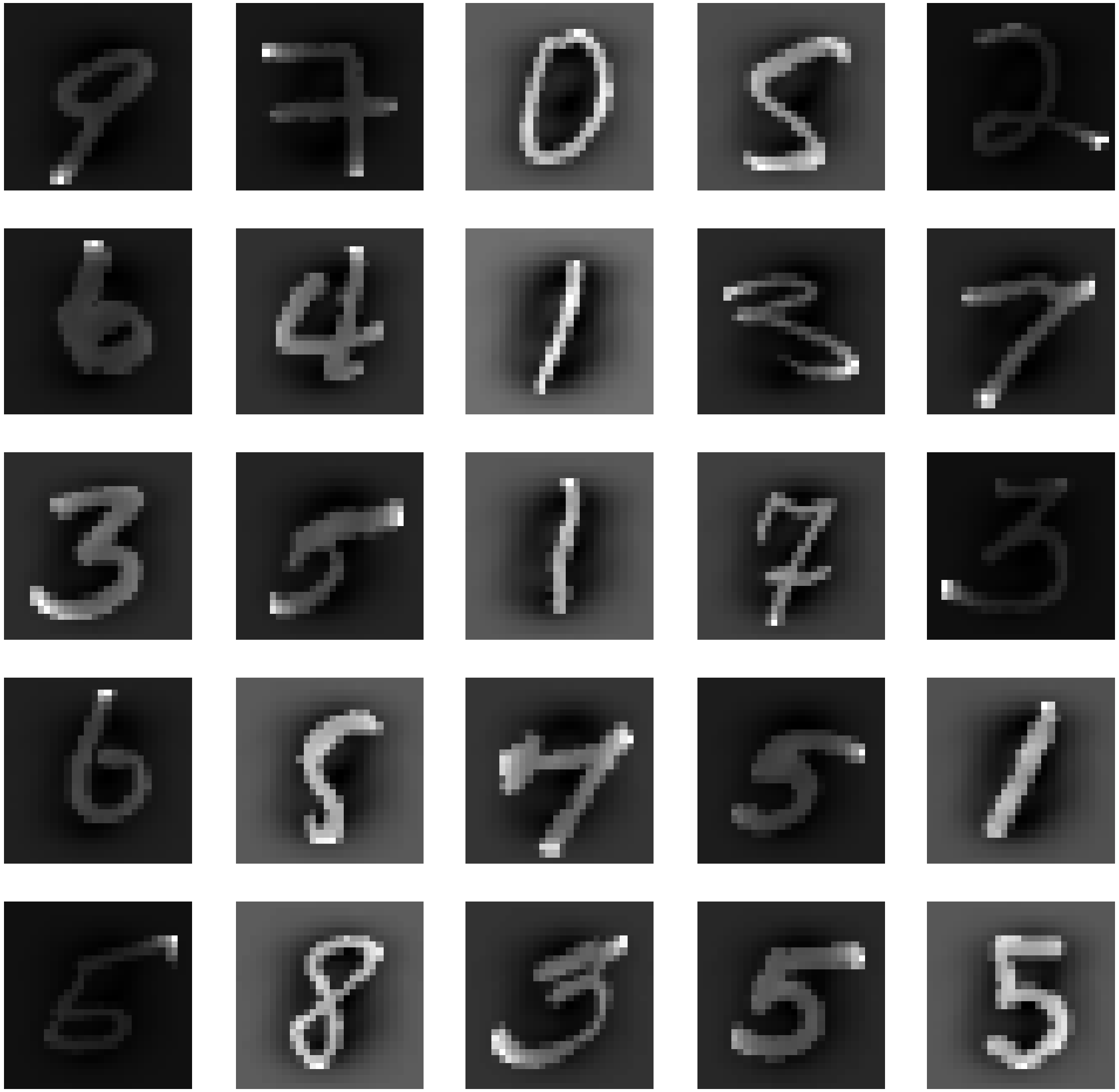
Here's the training data

In [5]:
```
mnh.setup()
mnh.visualize()
```

```
Retrieving MNIST_784 from cache
```

Out[5]:

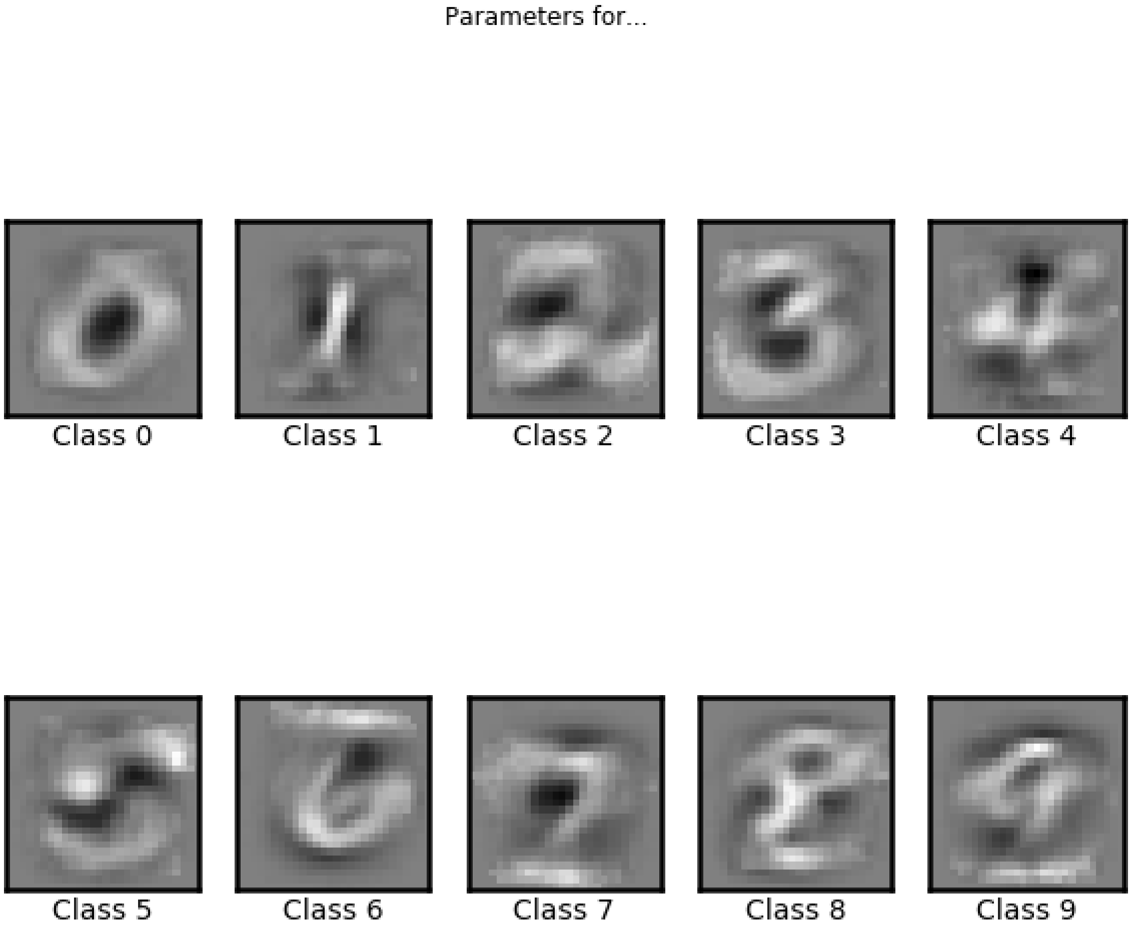




Let's fit a `LogisticRegression` model and examine the templates (coefficients $\Theta$)

In [6]:

```
_= mnh.fit()
mnist_fig, mnist_ax = mnh.plot_coeff()
```



Recall

- There is one parameter per pixel
- The parameters are ordered in the same way as the linearization of the pixels
    - from $(28 \times 28)$ grid to a vector of 784 numbers.
- We can display the 784 parameters in a $(28 \times 28)$ image to show the intensity of parameter associated with a pixel
- White is high parameter value; Black is low (or negative)

- The template for $0$ emphasizes small values (absence of bright pixels) in the center of the image
- The template for $1$ emphasizes bright vertical pixels
- The template for $8$ emphasizes the absence of bright pixels
    - in the two circles
    - in the pinched waist

You can now imagine how these templates might lead to misclassification

What is the classification of

- a "7" with a strong vertical line in the center (that's what the "1" template tries to match)
- a thin "0" (the "0" template is looking for a large donut)

So interpretation is a very powerful diagnostic tool for both understanding and improving your models.

In [7]:

```
print("Done")
```

Done