

```
In [20]: # Initialize Otter
import otter
grader = otter.Notebook("lab5.ipynb")
```

Lab 5: Modeling and Estimation

In this lab you will work with the tips dataset in order to:

1. Implement a basic model, define loss functions
2. Minimize loss functions using numeric libraries

Setup

```
In [21]: %matplotlib inline
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
np.random.seed(42)
plt.style.use('fivethirtyeight')
sns.set()
sns.set_context("talk")
```

Loading the Tips Dataset

To begin with, we load the tips dataset from the `seaborn` library. The tips data contains records of tips, total bill, and information about the person who paid the bill.

```
In [22]: data = sns.load_dataset("tips")

print("Number of Records:", len(data))
data.head()
```

Number of Records: 244

```
Out[22]:
```

	total_bill	tip	sex	smoker	day	time	size
0	16.99	1.01	Female	No	Sun	Dinner	2
1	10.34	1.66	Male	No	Sun	Dinner	3
2	21.01	3.50	Male	No	Sun	Dinner	3
3	23.68	3.31	Male	No	Sun	Dinner	2
4	24.59	3.61	Female	No	Sun	Dinner	4

Question 1: Defining the Model

In this lab we will attempt to model the tip value (in dollars) as a function of the total bill. As a consequence we define the following mathematical model:

$$\text{Tip} = \theta^* \times \text{TotalBill}$$

This follows the similar intuition that tips are some **unknown** percentage of the total bill. We will then try to estimate the slope of this relationship which corresponds to the percent tip.

Here the parameter θ^* represents the true percent tip that we would like to estimate.

Implement the python function for this model (yes this is very easy):

```
In [23]: def model(theta, total_bill):
        """
        Takes the parameter theta and the total bill, and returns the computed t

        Parameters
        -----
        theta: tip percentage
        total_bill: total bill value in dollars
        """
        return theta * total_bill
```

```
In [24]: grader.check("q1")
```

Out [24]: q1 passed! ✨

Loss Functions

A loss function is what we use to compare different outcomes $f(\theta)$ given some value of θ . (In lecture, some examples of variable θ were portfolio allocation, amount of goods in a transportation problem, etc.)

Recall that, in the movie recommender system, we minimized *squared error of estimated movie ratings*: i.e.,

$$\min_{U,V} \left\{ \sum_{i=1}^I \sum_{m=1}^M (r_{im} - \hat{r}_{im})^2 \right\} = \min_{U,V} \left\{ \sum_{i=1}^I \sum_{m=1}^M (r_{im} - u_i^T v_m)^2 \right\},$$

where U and V jointly are the variables. Note that we compute the discrepancy between estimated ratings ($\hat{r}_{im} = u_i^T v_m$) and observed rating r_{ij} by the sum of squared errors. This is also called the squared-loss.

In this lab we will study the *choice of the squared loss vs. the absolute loss functions* when finding the θ that explains data the *best*. In this tips data, x and y are given, and we want to find the best θ . **Hence, θ is the variable.**

Suppose for a given total bill x , we observe a tip value of y and our model predicts a tip value \hat{y} by:

$$\hat{y} = \theta x$$

then any of the following might be appropriate **loss functions**

1. **Squared Loss** (also known as the L^2 loss pronounced "ell-two"):

$$L(y, \hat{y}) = (y - \hat{y})^2$$

1. **Absolute Loss** (also known as the L^1 loss pronounced "ell-one"):

$$L(y, \hat{y}) = |y - \hat{y}|$$

In this lab we will compute two *best* θ 's. They are,

1. The *best* θ in **squared loss-sense**
2. The *best* θ in **absolute loss-sense**

Question 2a: Implement the squared loss function

In this question, you are going to define functions for **squared loss** and **absolute loss**.

$$L(y, \hat{y}) = (y - \hat{y})^2$$

Using the comments below, implement the squared loss function. Your answer should not use any loops.

```
In [25]: def squared_loss(y_obs, y_hat):
        """
        Calculate the squared loss of the observed data and predicted data.

        Parameters
        -----
        y_obs: an array of observed values
        y_hat: an array of predicted values

        Returns
        -----
        An array of loss values corresponding to the squared loss for each prediction
        """
        return (y_obs - y_hat) ** 2
```

```
In [26]: grader.check("q2a")
```

```
Out [26]: q2a passed! 🎉
```

Question 2b: Plotting Squared Loss

Suppose you observe a bill of \$28 with a tip \$3. (Does this tip look reasonable?)

Transform this information in our model, we have a $y = 3.00$ and $x = 28.00$. Now suppose we pick an initial range of θ 's (tip percent in this case) for you. Use the `model` and `squared_loss` function defined above to plot the loss for a range of θ values:

```
In [27]: y = 3.00
x = 28.00
thetas = np.linspace(0, 0.3, 200) # A range of theta values

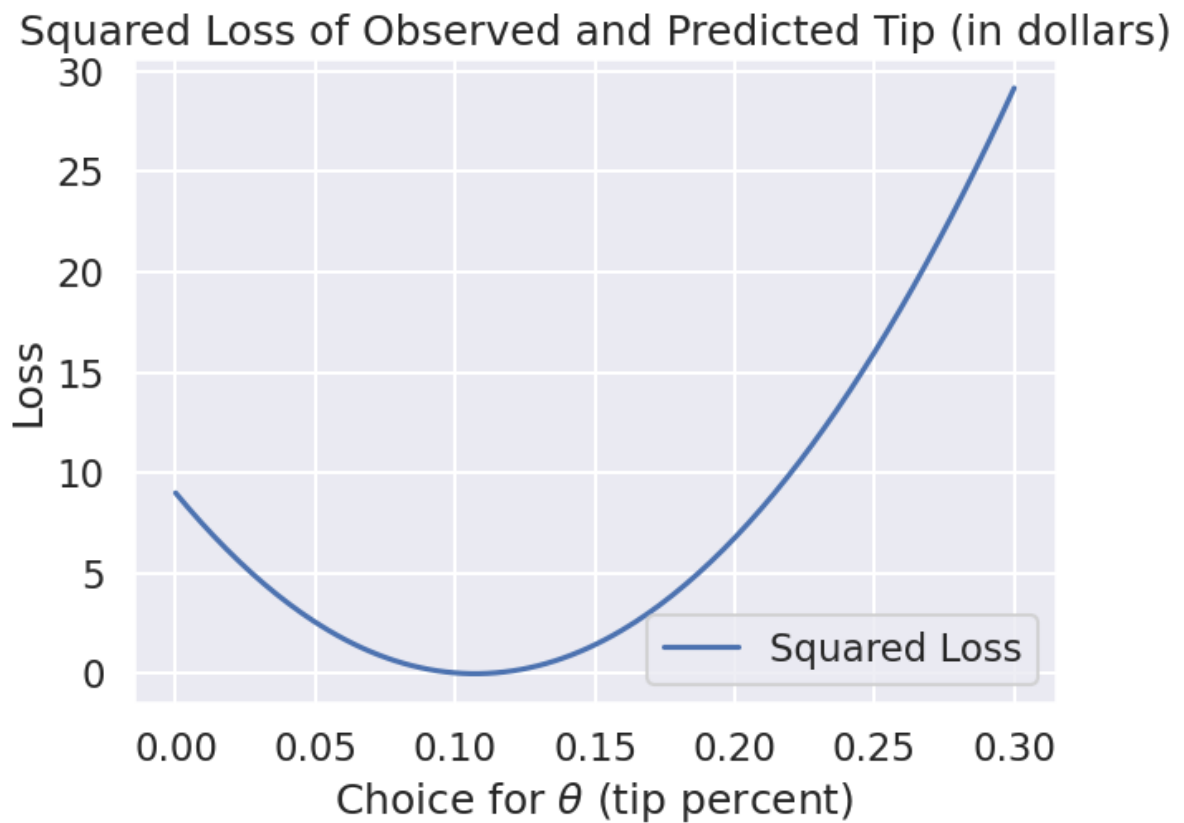
## Finish this by replacing 0.0 with the correct calculation
## Hint: You will use squared_loss y, model, theta and x
#loss should be a numpy array where the ith entry corresponds to the loss for
loss = np.array([ 0.0 for theta in thetas])

loss = np.array([squared_loss(y, model(theta, x)) for theta in thetas])
```

```
In [28]: grader.check("q2b")
```

```
Out [28]: q2b passed! 🏆
```

```
In [29]: plt.plot(thetas, loss, label="Squared Loss")
plt.title("Squared Loss of Observed and Predicted Tip (in dollars)")
plt.xlabel(r"Choice for $\theta$ (tip percent)")
plt.ylabel(r"Loss")
plt.legend(loc=4)
plt.savefig("squared_loss_my_plot.png", bbox_inches = 'tight')
```



Question 2c: Implement the absolute loss

$$L(y, \hat{y}) = |y - \hat{y}|$$

```
In [30]: def abs_loss(y_obs, y_hat):
        """
        Calculate the absolute loss of the observed data and predicted data.

        Parameters
        -----
        y_obs: an array of observed values
        y_hat: an array of predicted values

        Returns
        -----
        An array of loss values corresponding to the absolute loss for each predicted value.
        """
        return np.abs(y_obs - y_hat)
```

```
In [31]: grader.check("q2c")
```

```
Out[31]: q2c passed! 🌈
```

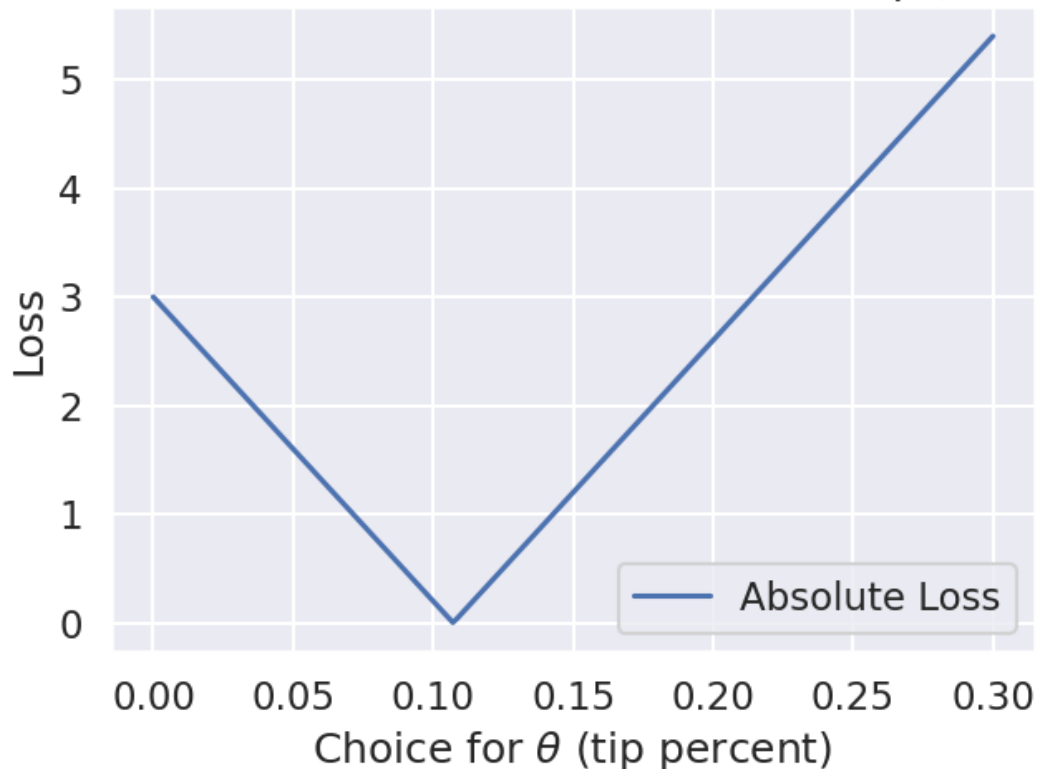
Below is the plot of the absolute loss.

```
In [32]: y = 3.00
x = 28.00
thetas = np.linspace(0, 0.3, 200)

# Code provided for you this time. (you're welcome)
loss = np.array([abs_loss(y, model(theta,x)) for theta in thetas])

plt.plot(thetas, loss, label="Absolute Loss")
plt.title("Absolute Loss of Observed and Predicted Tip (in dollars)")
plt.xlabel(r"Choice for $\theta$ (tip percent)")
plt.ylabel(r"Loss")
plt.legend(loc=4)
plt.savefig("absolute_loss_my_plot.png", bbox_inches = 'tight')
```

Absolute Loss of Observed and Predicted Tip (in dollars)



Question 2d: Plotting **Average Loss** for our Data

Remember we define our model to be:

$$\hat{y} = \theta x$$

Now, we can extend the above loss functions to an entire dataset by taking the average.

Let the dataset \mathcal{D} be the set of observations:

$$\mathcal{D} = \{(x_1, y_1), \dots, (x_n, y_n)\}$$

where x_i is the total bill and y_i is the tip dollar amount.

We can define the average loss over the dataset as:

$$L(\theta, \mathcal{D}) = \frac{1}{n} \sum_{i=1}^n L(m_{\theta}(x_i), y_i) = \frac{1}{n} \sum_{i=1}^n L(\theta x_i, y_i) = \frac{1}{n} \sum_{i=1}^n$$

where $m_{\theta}(x_i) = \theta x_i = \hat{y}_i$ is the model evaluated using the parameters θ on the bill amount x_i .

Complete the following code block to render a plot of the average absolute and squared loss for different values of θ

```
In [33]: thetas = np.linspace(0, 0.3, 200) # A range of theta values
y = data['tip']
x = data['total_bill']

# Replace 0.0 with the correct value computed
# Use the model and loss functions from above

# This time, each loss array should be a numpy array where the ith entry cor
# average loss across all data points for the ith theta

avg_squared_loss = np.array([np.mean(squared_loss(y, model(theta, x))) for t
avg_absolute_loss = np.array([np.mean(abs_loss(y, model(theta, x))) for thet
```

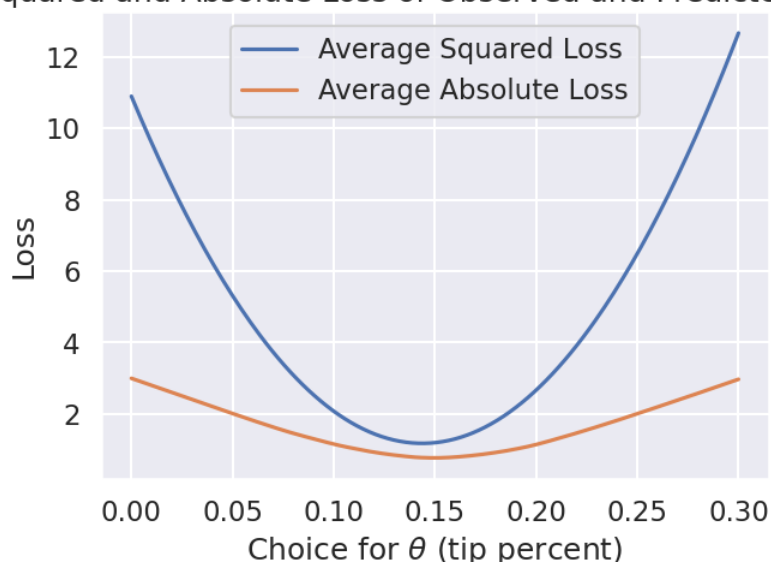
To test your loss calculations, run the cell below. If your code was correct, the following plot should look like:

 Average Loss

Note: Your colors might be different.

```
In [34]: plt.plot(thetas, avg_squared_loss, label = "Average Squared Loss")
plt.plot(thetas, avg_absolute_loss, label = "Average Absolute Loss")
plt.title("Average Squared and Absolute Loss of Observed and Predicted Tip (
plt.xlabel(r"Choice for $\theta$ (tip percent)")
plt.ylabel(r"Loss")
plt.legend()
plt.savefig("average_loss_my_plot.png", bbox_inches = 'tight')
```

Average Squared and Absolute Loss of Observed and Predicted Tip (in dollars)



Based on the plot above, approximately what is the optimal value of theta you would choose for this model?

In [35]: q2d2 = "0.15"

Question 3: Minimizing The Loss

In class, we used calculus to make improvements to our solution until convergence; however, there are specialized functions that are specifically designed to compute θ that minimize the loss function. In this lab we will use computational techniques to minimize the loss. Here we will use the `scipy.optimize.minimize` routine to minimize the average loss.

Complete the following python function:

```
In [36]: from scipy.optimize import minimize

def minimize_average_loss(loss_function, model, x, y):
    """
    Minimize the average loss calculated from using different thetas, and
    find the estimation of theta for the model.

    Parameters
    -----
    loss_function: A loss function, can be the squared or absolute loss func
    model: A defined model function, here we use the model defined above
    x: the x values (total bills)
    y: the y values (tip amounts)

    Returns
    -----
    The estimation for theta (tip percent) as a scalar
```


Note we will ignore failed convergence for this lab ...


```
## Notes on the following function call which you need to finish:
#
# 0. the ... should be replaced with the average loss evaluated on
#     the data x, y using the model and appropriate loss function
# 1. x0 is the initial value for THETA. Yes, this is confusing
#     but people who write optimization libraries like to use x
#     as the variable name to optimize, not theta.
```

```
avg_loss = np.mean(loss_function(y, model(theta=0.0, total_bill=x)))
```

```
return minimize(lambda theta: np.mean(loss_function(y, model(theta, x))))
```

In [37]: `grader.check("q3")`

Out[37]: **q3** passed! 🌟

To double-check your work, the cell below will rerun all of the autograder tests.

In [38]: `grader.check_all()`

Out[38]: q1 results: All test cases passed!

q2a results: All test cases passed!

q2b results: All test cases passed!

q2c results: All test cases passed!

q3 results: All test cases passed!

Submission

1. Save file to confirm all changes are on disk
2. Run *Kernel > Restart & Run All* to execute all code from top to bottom
3. Save file again to write any new output to disk
4. Select *File > Save and export Notebook as > HTML*.
5. Open in Google Chrome and print to PDF.
6. Submit to Gradescope