

# Building ML Models

Week 5 – Autodiff and  
Gradient Descent Review

# Autodiff Review

# Autodiff Review

- We created this autodiff library, what does it actually do?

## Autodiff Review: Expression

- `expression` is the base class. As the purest form, it represents a single variable.
- You create an instance of it by doing:

```
x = expression("x")
```

Python variable  
name

Object type

Autodiff  
variable name

## Autodiff Review: Constant

- `constant` is another fundamental class. It represents a constant value, like 10.
- You create an instance of it by doing:

```
one = constant(1)
```

Python variable  
name

Object type

Constant  
value

## Autodiff Review: Combining Expressions

- We can combine multiple of these expressions together with basic math operations:

```
two = constant(2)
x = expression("x")
two_x = two * x
```

This will implicitly create a `multiplication` object, which will be storing the `expression`  $2x$

## Autodiff Review: Evaluating Expressions

- We can evaluate expressions with the `eval` function:

```
result = two_x.eval({"x": 10})
```

Note: we need to pass in a dictionary telling the autodiff library what the values of our `expressions` are.

## Autodiff Review: Differentiating

- We can differentiate expressions with the `diff` function:

```
result = two_x.diff({"x": 10}, "x")
```

Note: we need to pass in a dictionary telling the autodiff library what the values of our `expressions` are AND what variable we need to differentiate with respect to.

Think: why do we need to pass in the values?



# Gradient Descent Review

## Gradient Descent Review

- We've talked about the formulas a lot for gradient descent, but what does that look like when training an actual model?

## Gradient Descent Review: Training

- When trying to train a regression model, we pass in a set of data to fit on, and the expected outputs
- For each set of that data, we calculate what our model would predict with this formula:

$$\hat{Y} = m_1x_1 + m_2x_2 + \dots + b$$

# Gradient Descent Review: Updating Params

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- We need to somehow tell the model how far off it is, and update its parameters

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- We need to somehow tell the model how far off it is, and update its parameters
- We do this via mean-squared error

# Gradient Descent Review: Updating Params

- We calculate how “far off” the model is via this formula:

$$MSE(\hat{Y}, Y) = \frac{1}{n} \sum_{i=1}^n (\hat{Y} - Y)^2$$

$\hat{Y}$  is what the model outputs,  $Y$  is the true value

## Gradient Descent Review: Updating Slopes

- We can use MSE to update the slopes:

$$\Delta m_i = -\frac{\partial}{\partial m_i} MSE(\hat{Y}, Y)$$

Note how this is only for a single slope value, for a single sample of our training data. We need to accumulate this loss across all samples separately, for *each* slope value.

## Gradient Descent Review: Updating Y-int

- Updating the y-intercept is mostly the same:

$$\Delta b = -\frac{\partial}{\partial b} MSE(\hat{Y}, Y)$$

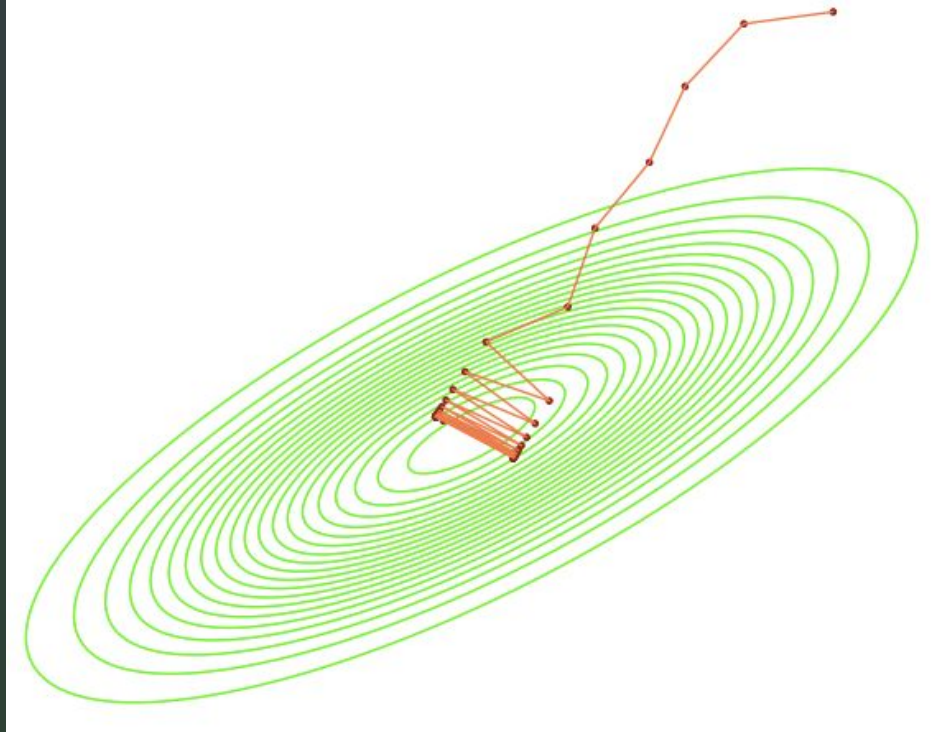
Recall from last week: we only need to keep track of a *singular* y-intercept value.



## Gradient Descent Review: Oscillation

- When we're updating the weights in gradient descent, we don't want to keep overshooting our target
- This is why a learning rate is introduced, to prevent oscillation
- Otherwise, our weights would never converge
- Multiply the final updated delta values by this learning rate

# Gradient Descent Review: Oscillation



# Overview of Linear Regression Code

## Linear Regression Code: Member Variables

- `self.mx`: a dictionary with string keys "m0", "m1", ... to "mN", N is the number of slope variables
- `self.yint`: the y-intercept value

! Actual **values**, not just autodiff expressions !

## Linear Regression Code: fit()

- `fit()` takes in 4 parameters, `X_fit`, `y_fit`, `n_epochs`, and `learning_rate`
- `X_fit`: a dataframe to train the model on
- `y_fit`: the expected y-values for each row of `X_fit`
- `n_epochs` the number of iterations you'll iterate for in gradient descent
- `learning_rate`: the factor to multiply the losses by

## Linear Regression Code: fit() TODOs

- Create `prediction_expr`, which is  $m_0 * x_0 + m_1 * x_1 + \dots + y_{int}$ 
  - Hint: you can get the specific row/column element in a dataframe by doing `X_fit.iloc[row, column]`
- Gradient descent: store the current loss values for each slope variable and the y-intercept
  - Hint: we need to iterate through each of the keys in `self.mx`, what do we need to differentiate with respect to?

## Linear Regression Code: fit() TODOs

- Update `self.mx` and `self.yint`
  - Use the learning rate and the gradients you've calculated for that epoch to update the slope variables you stored previously

## Linear Regression Code: `predict()`

- `predict()` takes in one parameter
- `X_pred` is a dataframe of the data we want to predict the y-values for



## Linear Regression Code: predict() TODOs

- Prediction calculation. Use the formula  $y = m_0 * x_0 + m_1 * x_1 + \dots + y_{int}$  to predict a y-value and add it to the `predictions` list.
  - Hint: did we use this formula anywhere else?

# Autodiff Exercises

# Autodiff Exercises

- [GitHub](#)
- [Jupyter Notebook](#)