ECON 8310 - Business Forecasting

Instructor:

Dustin White

Mammel Hall 332G

Office Hours:

By appointment (remote or live options available)

Contact Info:

drwhite@unomaha.edu

Quick Note

Your ability to use code to solve problems will be the basis for your grade in this course, so if you cannot commit the time to practice coding, you are not likely to pass this class.

Grade Details

Score	Grade	Score	Grade
>94%	A	72.5-77.4	C
90-93.9	A-	70-72.4	C-
87.5-89.9	B+	62.5-69.9	D
82.5-87.4	B	60-62.5	D-
80-82.4	B-	<60	F
77.5-79.9	C+		

Grade Details

Assignment	Percent of Grade
Lab Work	30%
Reading Assignments	20%
Participation	20%
Course Project	20%

My Expectations

- Plan on spending **all of our time in lab** working on homework and projects and refining your predictions
- **Take charge** of your assignments and projects; they will be open-ended!

Expectations of Me

- I will work through examples of code in class
- I will be available during lab and office hours to help you with assignments
- I will revise the course material as needed to suit your interests
    - Just added a bunch of new models last spring!

Introduction to Forecasting

What is Forecasting?

Forecast: "to predict or estimate (a future event or trend)" -- Google Dictionary

- Predict weather patterns
- Estimate the quantity of stock required during a certain time-span
- Generally, determine the most likely outcome of a stochastic process based on previous events
- **Learn from patterns**

Forecasting is just fancy trendlines

In this course, we want to learn how to predict outcomes based on the information that we already possess.

Forecasting

- Time Series modeling
- Predictive modeling using machine learning
- Neural Networks
- Bayesian models for complex processes
- **Choosing the best model for the job**

Exponential Smoothing

For reference, read Hyndman and Athanasopoulos' Chapter 7

You know what they say about assumptions...

Today, let's talk about an assumption-free* model

*** almost assumption free...**

Small n, big problem

Let's say we are just getting started collecting data, and we have a very small number of observations, but still need to make a forecast?

- What if you just have, like, two observations or something?

We can generate some data and explore our first model

A random walk, simulated

```python
import numpy as np
import plotly.express as px

np.random.seed(seed=0)

def step(prev=0):
    return prev + np.random.normal(loc=0.05, scale=1.0)

def walk(steps=10):
    data = []
    for i in range(10):
        if i==0:
            data.append(step())
        else:
            data.append(step(data[i-1]))
    return data
```

Introducing...

Exponential Smoothing! A model that doesn't care what your data look like, or even how much you have!

Simple Smoothing

Our first version of this model is super simple:

1. Take a weighted average of the data
2. Forecast that value!

Simple Smoothing

How do we weight it? With α!

$$y_{t+1} = \alpha y_t + \alpha(1-\alpha)y_{t-1} + \alpha(1-\alpha)^2 y_{t-2} + \ldots$$

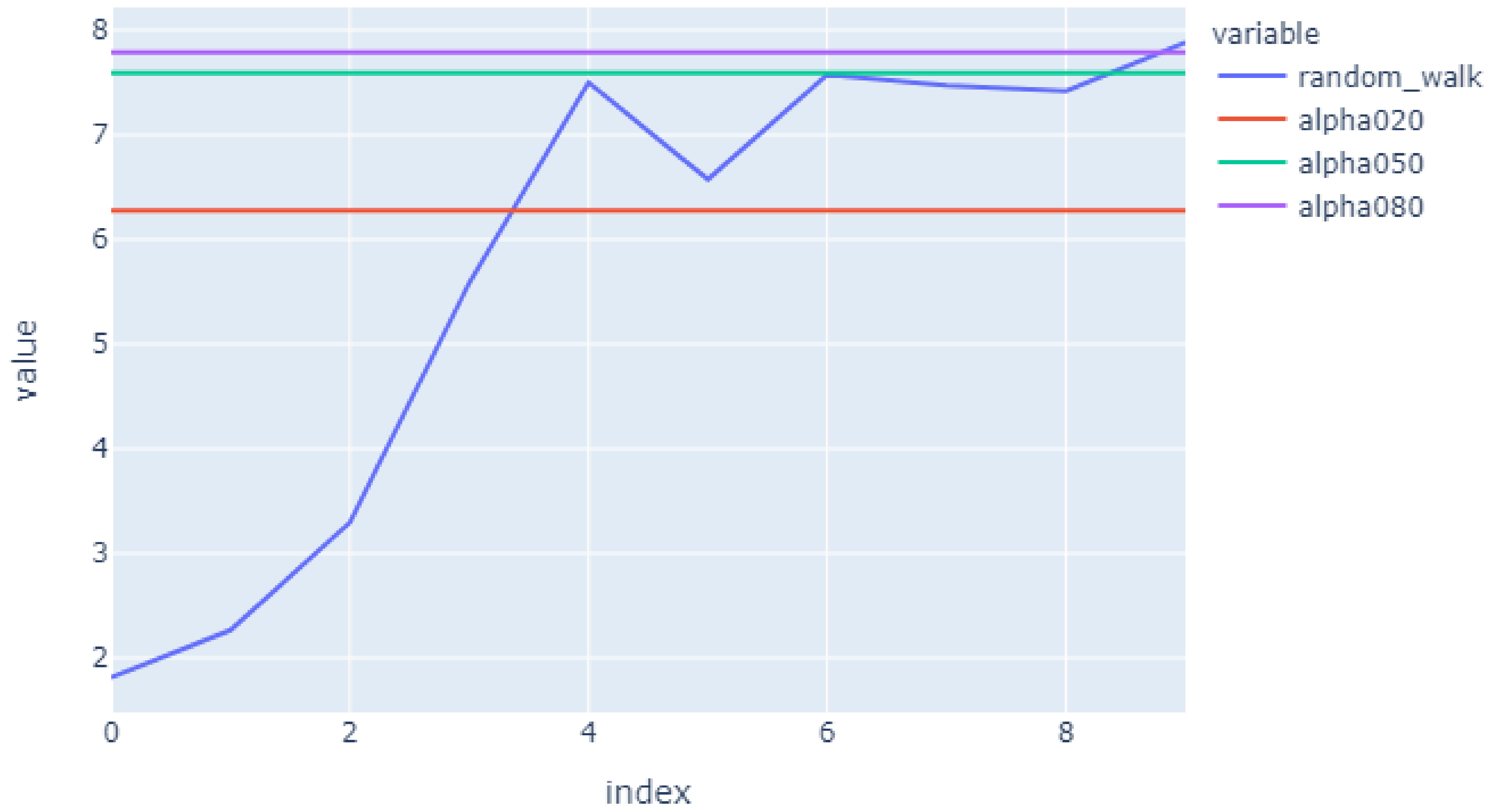
The weights on our model sum asymptotically to 1

Simple Smoothing - The Code

```
from statsmodels.tsa.api import ExponentialSmoothing
from statsmodels.tsa.api import SimpleExpSmoothing
import pandas as pd

data = walk(10)

alpha020 = SimpleExpSmoothing(data).fit(
                    smoothing_level=0.2,
                    optimized=False)

alpha050 = SimpleExpSmoothing(data).fit(
                    smoothing_level=0.5,
                    optimized=False)

alpha080 = SimpleExpSmoothing(data).fit(
                    smoothing_level=0.8,
                    optimized=False)

level2 = alpha020.forecast(1)
level5 = alpha050.forecast(1)
level8 = alpha080.forecast(1)

print(level2, level5, level8)
```

Simple Smoothing - The Code (#2)

```
levels = pd.DataFrame([data,
[float(level2) for i in range(10)],
[float(level5) for i in range(10)],
[float(level8) for i in range(10)]]).T

levels.columns = ['random_walk', 'alpha020', 'alpha050', 'alpha080']

px.line(levels, y=['random_walk', 'alpha020', 'alpha050', 'alpha080'])
```



variable
random_walk
alpha020
alpha050
alpha080
value
index
8
7
6
5
4
3
2
0
2
4
6
8

Solving problems!

Simple is good! The simplest model is to set $\alpha = 1$, so that we only care what the most recent value is, and use it as our forecast.

- Has the added advantage of working with $n = 1$!

We can also use an "unweighted" average ($\alpha = 0$)

Not enough usefulness

So that's cool and simple, but what if I want a forward-looking forecast?

- Exponential smoothing can cover you!

Smoothing plus Trendline

```
# Linear trend
trend = ExponentialSmoothing(data, trend='add').fit()

trends = pd.DataFrame([data + list(trend.forecast(10)), [0]*10 + [1]*10]).T
trends.columns = ['random_walk', 'forecast']

px.line(trends, y='random_walk', color='forecast')
```

Smoothed Trends

Just like we could smooth past values, we can also create a smoothed trendline to include in our forecast!

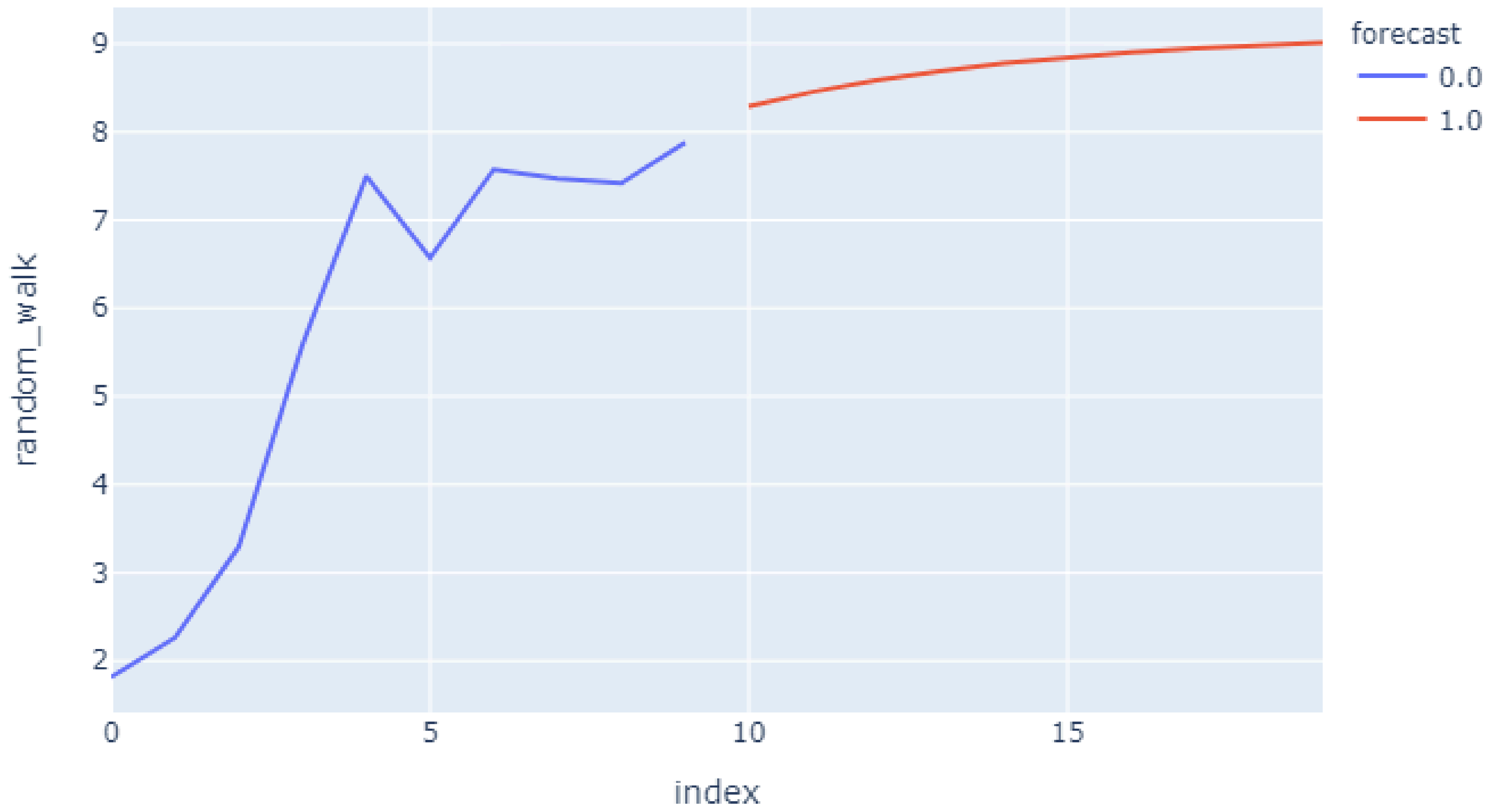
forecast
0.0
1.0
random_walk
index
14
12
10
8
6
4
2
0
5
10
15

If present trends continue...

We know they never do, so we can dampen (weaken) the trend over time

Damped Trends

```
# Linear trend WITH DAMPING
trend = ExponentialSmoothing(data, trend='add', damped=True).fit()

trends = pd.DataFrame([data + list(trend.forecast(10)), [0]*10 + [1]*10]).T
trends.columns = ['random_walk', 'forecast']

px.line(trends, y='random_walk', color='forecast')
```



forecast
0.0
1.0
random_walk
index
9
8
7
6
5
4
3
2
0
5
10
15

Seasonality? You got it!

Exponential Smoothing also allows for seasonality. While our current data doesn't have seasonal effects (it's a random walk), here is how we accomodate seasonality:

```
# Linear trend with seasonality
trend = ExponentialSmoothing(employment,
            trend='add',
            seasonal='add',
            seasonal_periods=12).fit()

# Linear trend with damping and seasonality
dampedTrend = ExponentialSmoothing(employment,
            trend='add',
            seasonal='add',
            damped=True,
            seasonal_periods=12).fit()
```

Lab Time!