Exponential Smoothing

For reference, read Hyndman and Athanasopoulos' Chapter 7

Non-parametrics, revisited

GAMs are great compromises between parametric and non-parametric modeling.

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

Small n, big problem

What happens to our previous models when we have a very small number of observations, and still need to make a forecast?

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

A random walk, simulated

```
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 really 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!

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

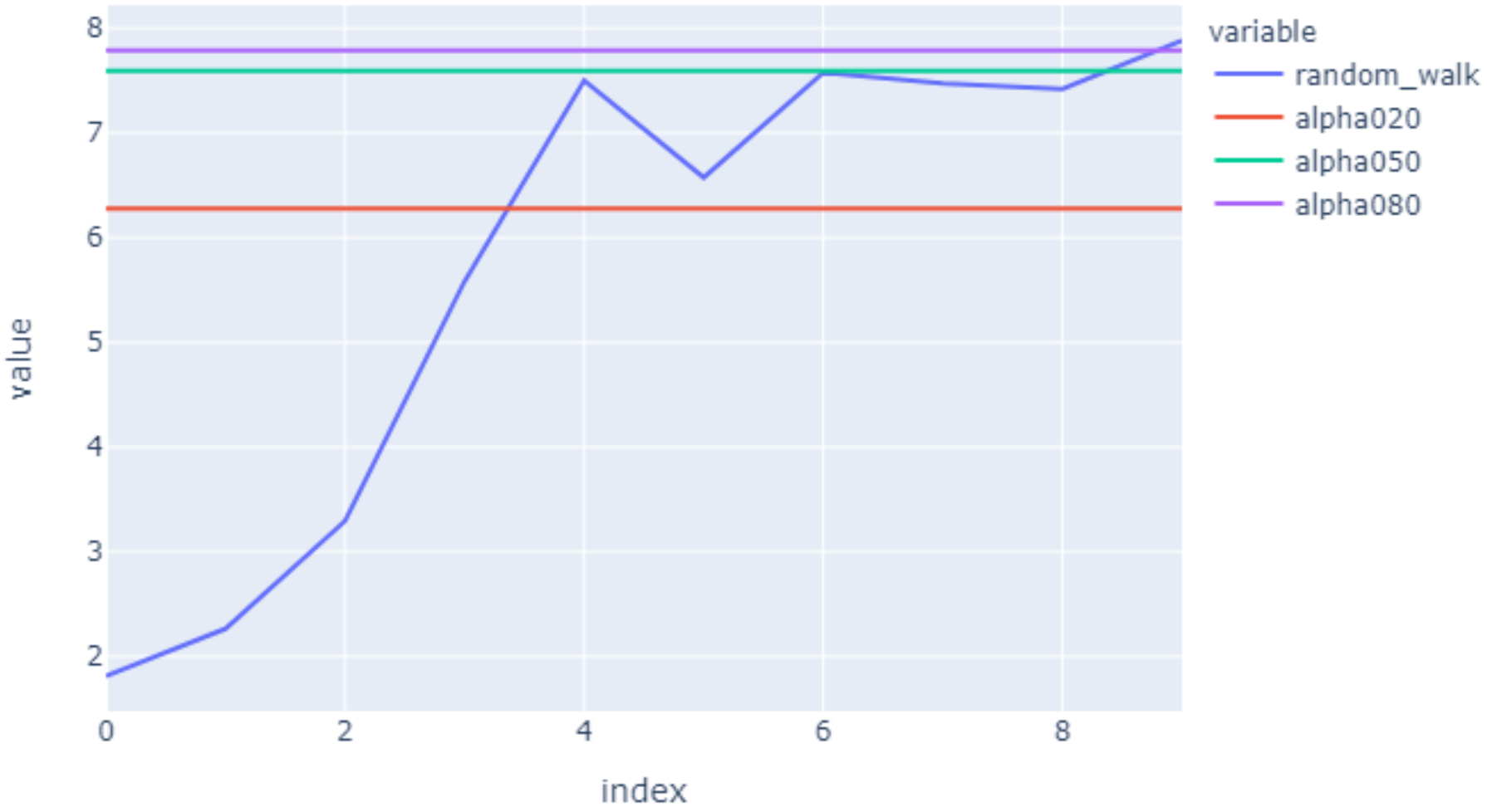
The weights on our model sum to ~1

Simple Smoothing - The Code

```
from statsmodels.tsa.api import ExponentialSmoothing, 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
0
2
4
6
8
2
3
4
5
6
7
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.

Not enough usefulness

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

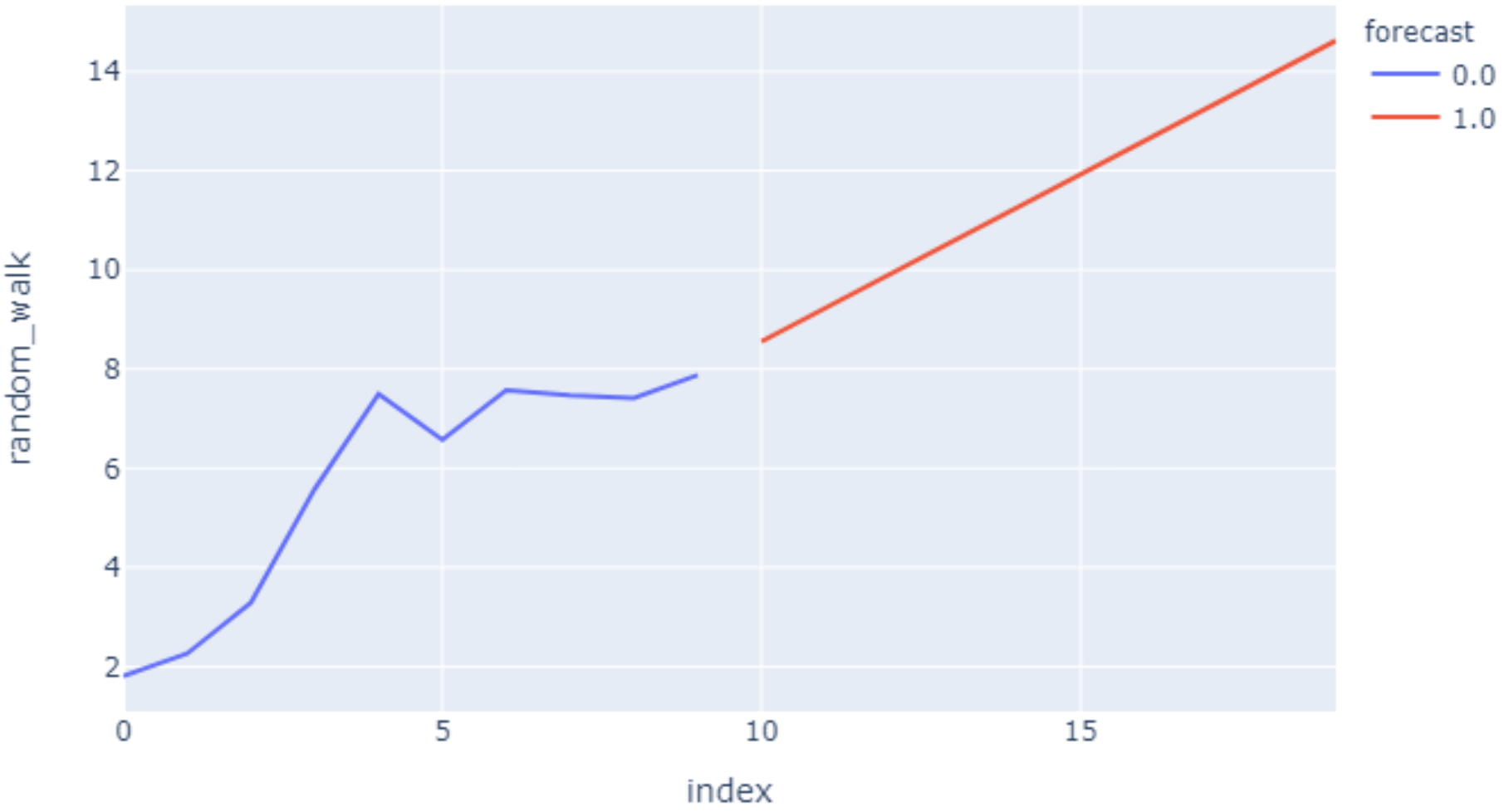
- Exponential smoothing can cover you!

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!

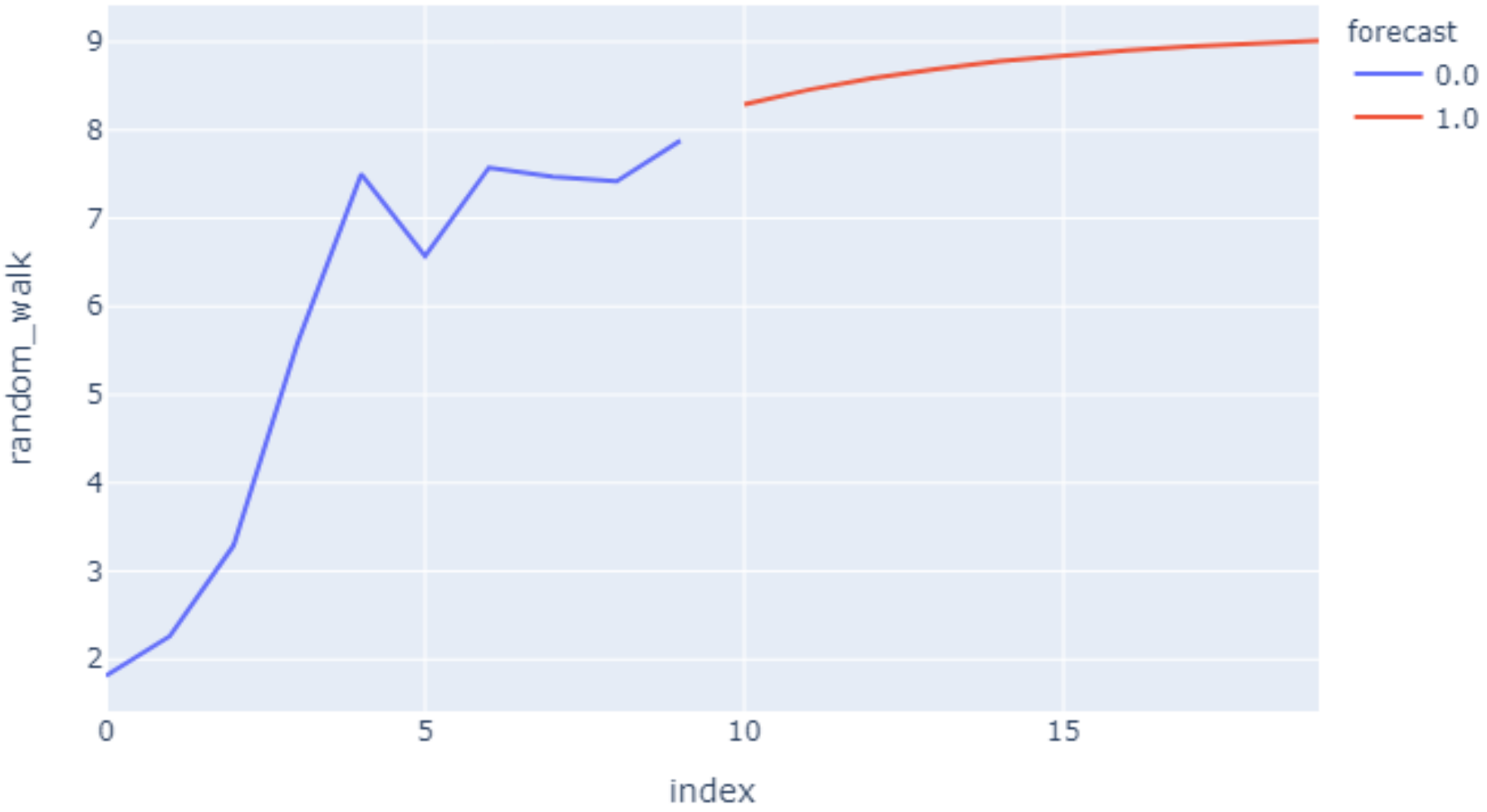

forecast
0.0
1.0
random_walk
14
12
10
8
6
4
2
0
5
10
15
index

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

Lab Time!