Working with time series data in pandas

CUSTOMER ANALYTICS AND A/B TESTING IN PYTHON

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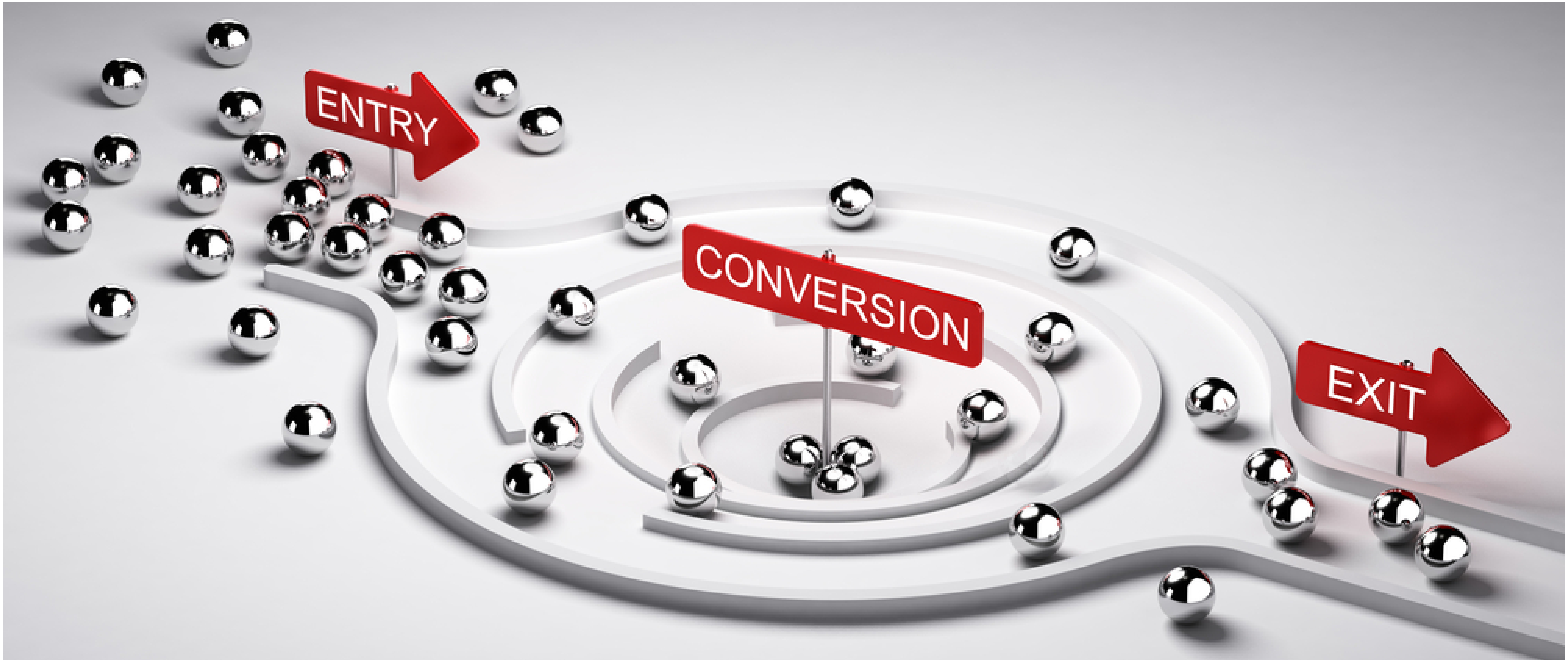
Exploratory Data Analysis

- Exploratory Data Analysis (EDA)
- Working with time series data
- Uncovering trends in KPIs over time

Review: Manipulating dates & times



Example: Week Two Conversion Rate

- **Week 2 Conversion Rate** Users who subscribe in the second week *after* the free trial
- Users must have:
    - Completed the free trial
    - **Not** subscribed in the first week
    - Had a full second week to subscribe or not

Using the Timedelta class

- **Lapse Date:** Date the trial ends for a given user

```
import pandas as pd
from datetime import timedelta


# Define the most recent date in our data
current_date = pd.to_datetime('2018-03-17')

# The last date a user could lapse be included
max_lapse_date = current_date - timedelta(days=14)

# Filter down to only eligible users
conv_sub_data = sub_data_demo[
    sub_data_demo.lapse_date < max_lapse_date]
```

Date differences

- Step 1: Filter to the relevant set of users
- **Step 2: Calculate the time between a users lapse and subscribed dates**

```
# How many days passed before the user subscribed
sub_time = conv_sub_data.subscription_date - conv_sub_data.lapse_date

# Save this value in our dataframe
conv_sub_data['sub_time'] = sub_time
```

Date components

- Step 1: Filter to the relevant set of users
- Step 2: Calculate the time between a users lapse and subscribed dates
- **Step 3: Convert the `sub_time` from a `timedelta` to an `int`**

```
# Extract the days field from the sub_time
conv_sub_data['sub_time'] = conv_sub_data.sub_time.dt.days
```

Conversion rate calculation

```
# filter to users who have did not subscribe in the right window
conv_base = conv_sub_data[(conv_sub_data.sub_time.notnull()) | \
    (conv_sub_data.sub_time > 7)]
total_users = len(conv_base)
```

```
total_subs = np.where(conv_sub_data.sub_time.notnull() & \
    (conv_base.sub_time <= 14), 1, 0)
total_subs = sum(total_subs)
```

```
conversion_rate = total_subs / total_users
```

```
0.0095877277085330784
```

Parsing dates - on import

```
pandas.read_csv(...,
    parse_dates=False,
    infer_datetime_format=False,
    keep_date_col=False,
    date_parser=None,
    dayfirst=False,...)
```

```
customer_demographics = pd.read_csv('customer_demographics.csv',
    parse_dates=True,
    infer_datetime_format=True)
```

```
    uid           reg_date          device  gender    country    age
0    54030035.0    2017-06-29        and          M        USA        19
1    72574201.0    2018-03-05        iOS          F        TUR        22
2    64187558.0    2016-02-07        iOS          M        USA        16
3    92513925.0    2017-05-25        and          M        BRA        41
4    99231338.0    2017-03-26        iOS          M        FRA        59
```

Parsing dates - manually

```
pandas.to_datetime(arg, errors='raise', ..., format=None, ...)
```

strftime

1993-01-27 -- `"%Y-%m-%d"`

05/13/2017 05:45:37 -- `"%m/%d/%Y %H:%M:%S"`

September 01, 2017 -- `"%B %d, %Y"`

Let's practice!

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Creating time series graphs with matplotlib

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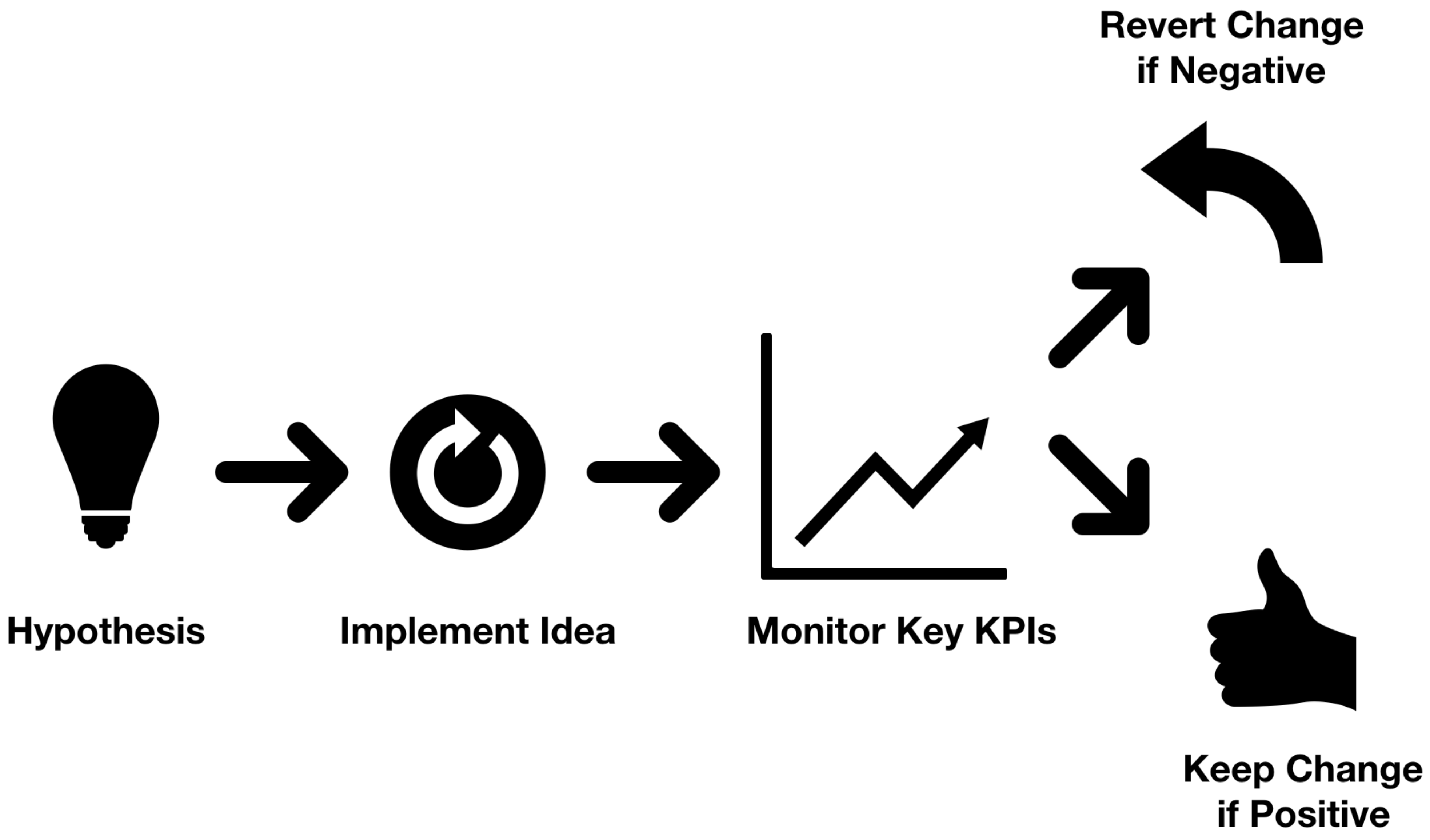
Conversion rate over time

Useful Ways to Explore Metrics

- By user type
- Over time

Monitoring the impact of changes



Week one conversion rate by day

```
import pandas as pd
from datetime import timedelta

# The maximum date in our dataset
current_date = pd.to_datetime('2018-03-17')


# Limit to users who have had a week to subscribe
max_lapse_date = current_date - timedelta(days=7)
conv_sub_data = sub_data_demo[
    sub_data_demo.lapse_date < max_lapse_date]


# Calculate how many days it took the user to subscribe
conv_sub_data['sub_time'] = (conv_sub_data.subscription_date
    - conv_sub_data.lapse_date.dt.days)
```

Conversion Rate by Day

- The lapse date is the first day a user is eligible to subscribe

```
# Find the convsersion rate for each daily cohort
conversion_data = conv_sub_data.groupby(
    by=['lapse_date'],as_index=False
).agg({'sub_time': [gc7]})

# Clean up the dataframe columns
conversion_data.head()
```

```
    lapse_date    sub_time
0    2017-09-01    0.224775
1    2017-09-02    0.223749
...
```

Plotting Daily Conversion Rate

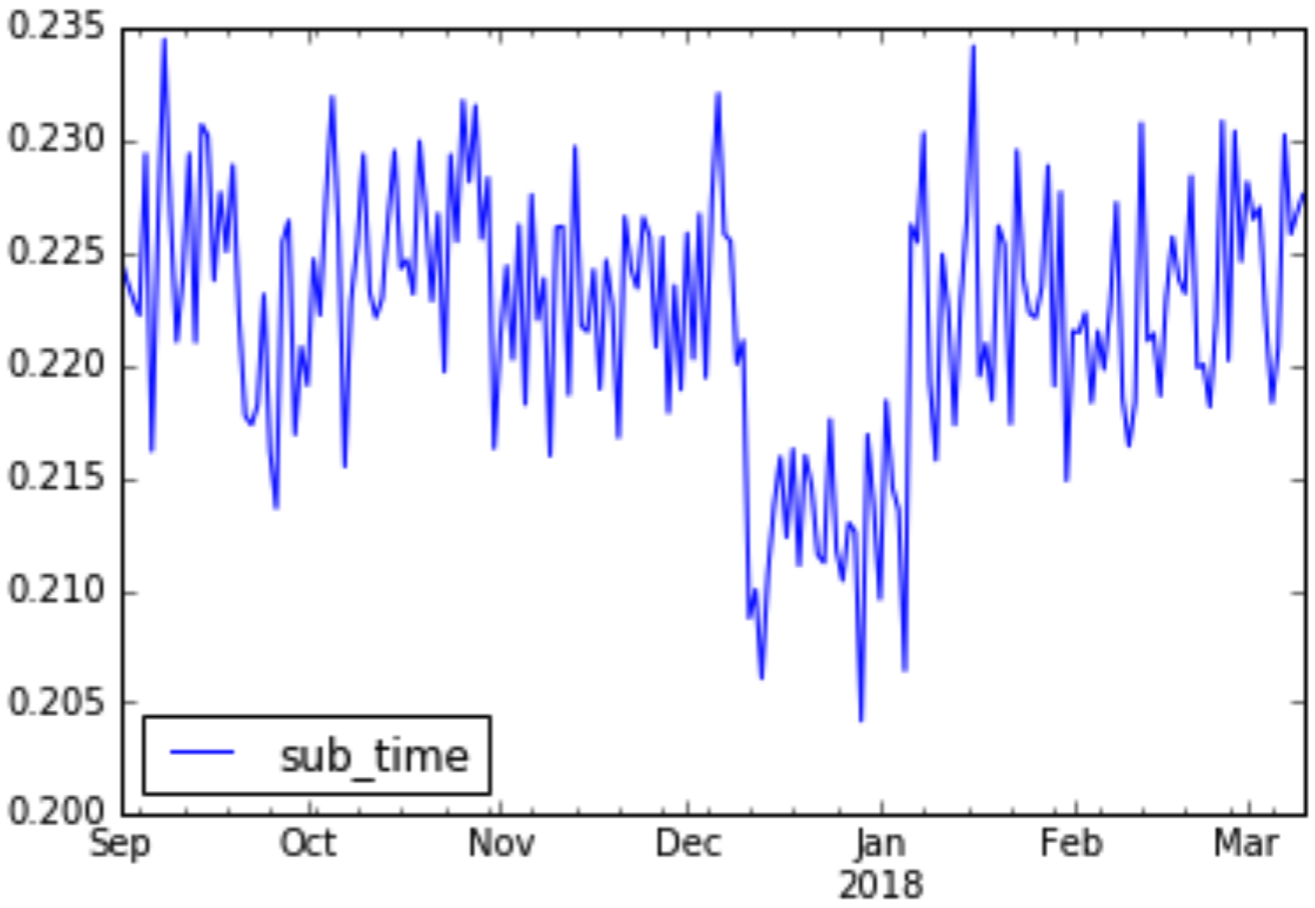
- Use the `.plot()` method to generate graphs of DataFrames

```
# Convert the lapse_date value from a string to a
# datetime value
conversion_data.lapse_date = pd.to_datetime(
    conversion_data.lapse_date
)


# Generate a line graph of the average conversion rate
# for each user registration cohort
conversion_data.plot(x='lapse_date', y='sub_time')
```

Plotting Daily Conversion Rate

```
# Print the generated graph to the screen
plt.show()
```



Trends in different cohorts

- See how changes interact with different groups
- Compare users of different genders
- Evaluate the impact of a change across regions
- See the impact for different devices

Trends across time and user groups

- Is the holiday dip consistent across different countries?

```
conversion_data.head()
```

  - Conversion rate by day, broken out by our top selling countries

```
    lapse_date    country    sub_time
0    2017-09-01    BRA        0.184000
1    2017-09-01    CAN        0.285714
2    2017-09-01    DEU        0.276119
3    2017-09-01    FRA        0.240506
4    2017-09-01    TUR        0.161905
```

Conversion rate by country

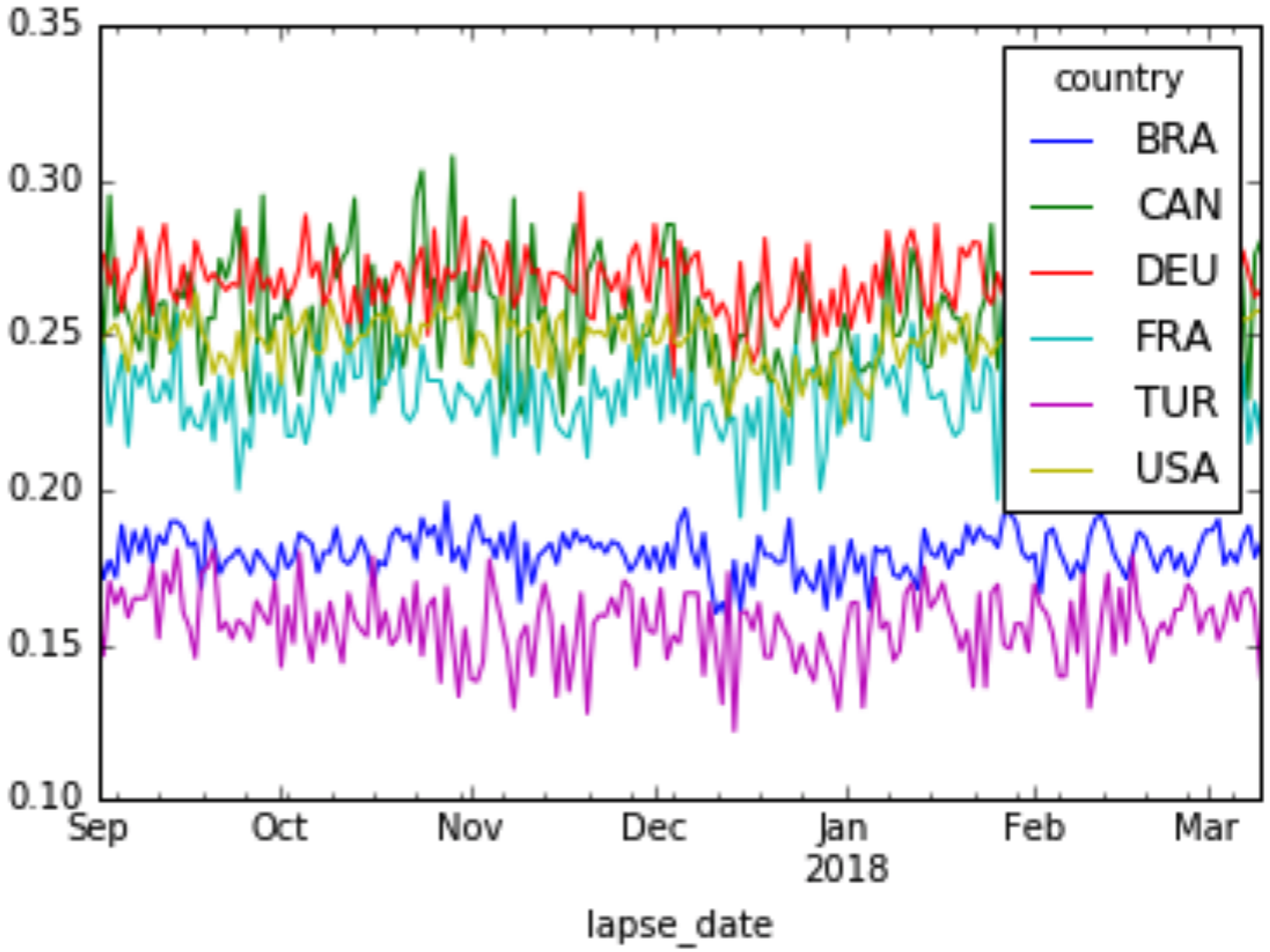
```
# Break out our conversion rate by country
reformatted_cntry_data = pd.pivot_table(
    conversion_data, # dataframe to reshape
    values=['sub_time'], # Our primary value
    columns=['country'], # what to break out by
    index=['reg_date'], # the value to use as rows
    fill_value=0
)
```

```
lapse_date         BRA        CAN        DEU
2017-09-01         0.184000   0.285714    0.276119    ...
2017-09-02         0.171296   0.244444    0.276190    ...
2017-09-03         0.177305   0.295082    0.266055    ...
```

Plotting trends in different cohorts

```
# Plot each countries conversion rate
reformatted_cntry_data.plot(
    x='reg_date',
    y=['BRA','FRA','DEU','TUR','USA','CAN']
)
```

```
plt.show()
```



Let's practice!

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Understanding and visualizing trends in customer data

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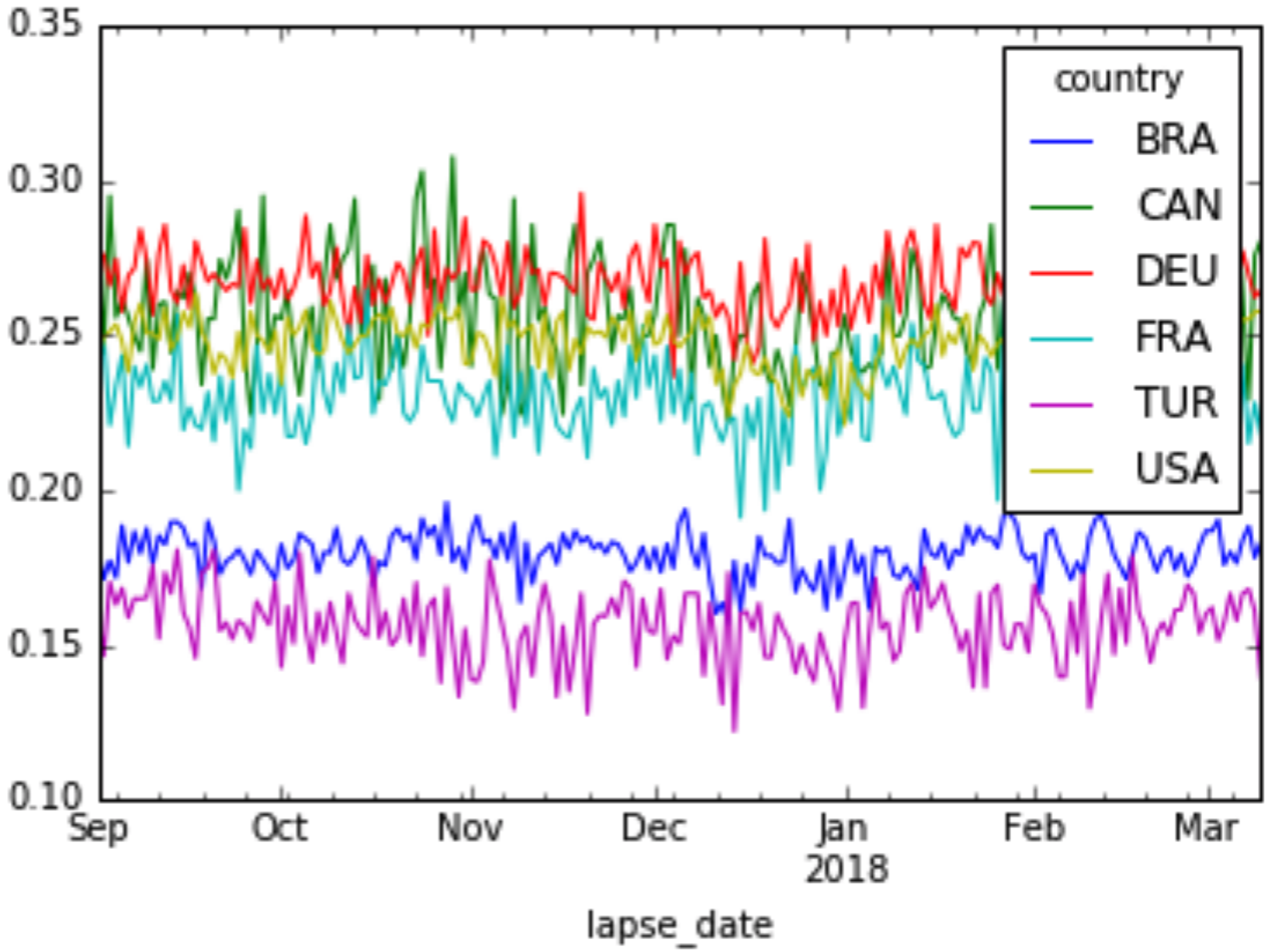
Further techniques for uncovering trends



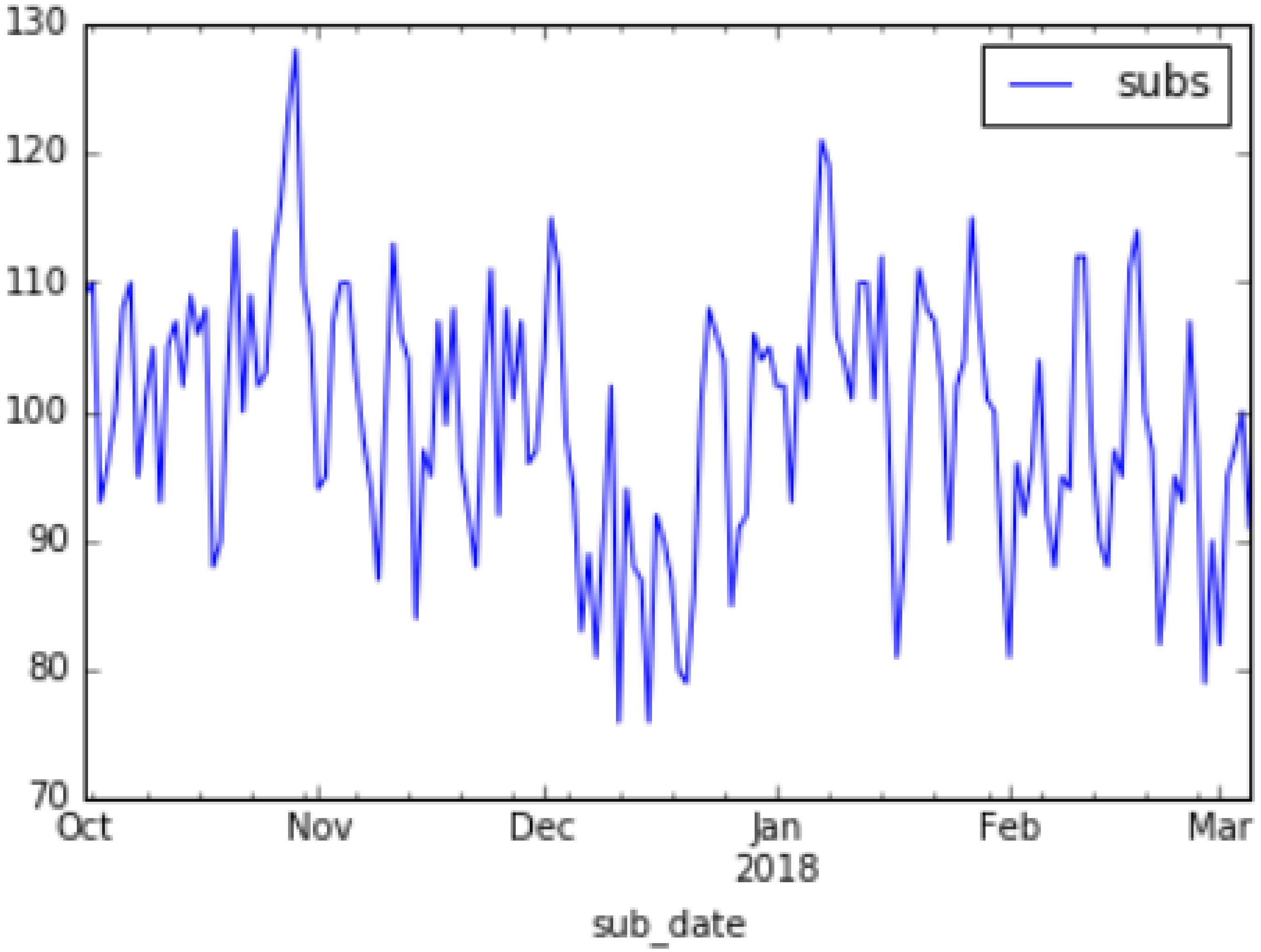
Subscribers Per Day

```
# Find the days-to-subscribe of our loaded usa subs data set
usa_subscriptions['sub_day'] = (usa_subscriptions.sub_date -
    usa_subscriptions.lapse_date).dt.days

# Filter out those who subscribed in the past week
usa_subscriptions = usa_subscriptions[usa_subscriptions.sub_day <= 7]

# Find the total subscribers per day
usa_subscriptions = usa_subscriptions.groupby(
    by=['sub_date'], as_index = False
).agg({'subs': ['sum']})
```

Weekly seasonality and our pricing change

```
# plot USA subscribcers per day
usa_subscriptions.plot(x='sub_date', y='subs')
plt.show()
```

- **Weekly Seasonality**: Trends following the day of the week
    - Potentially more likely to subscribe on the weekend
    - Seasonality can hide larger trends...the impact of our price change?



Correcting for seasonality with trailing averages

- **Trailing Average**: smoothing technique that averages over a **lagging window**
  - Reveal hidden trends by **smoothing** out seasonality
  - Average across the period of seasonality
  - 7-day window to smooth weekly seasonality
  - Average out day level effects to produce the average week effect

Calculating Trailing Averages

- Calculate the rolling average over the USA subscribers data with `.rolling()`
  - Call this on the `Series` of interest
  - `window` : Data points to average
  - `center` : If true set the average at the center of the window

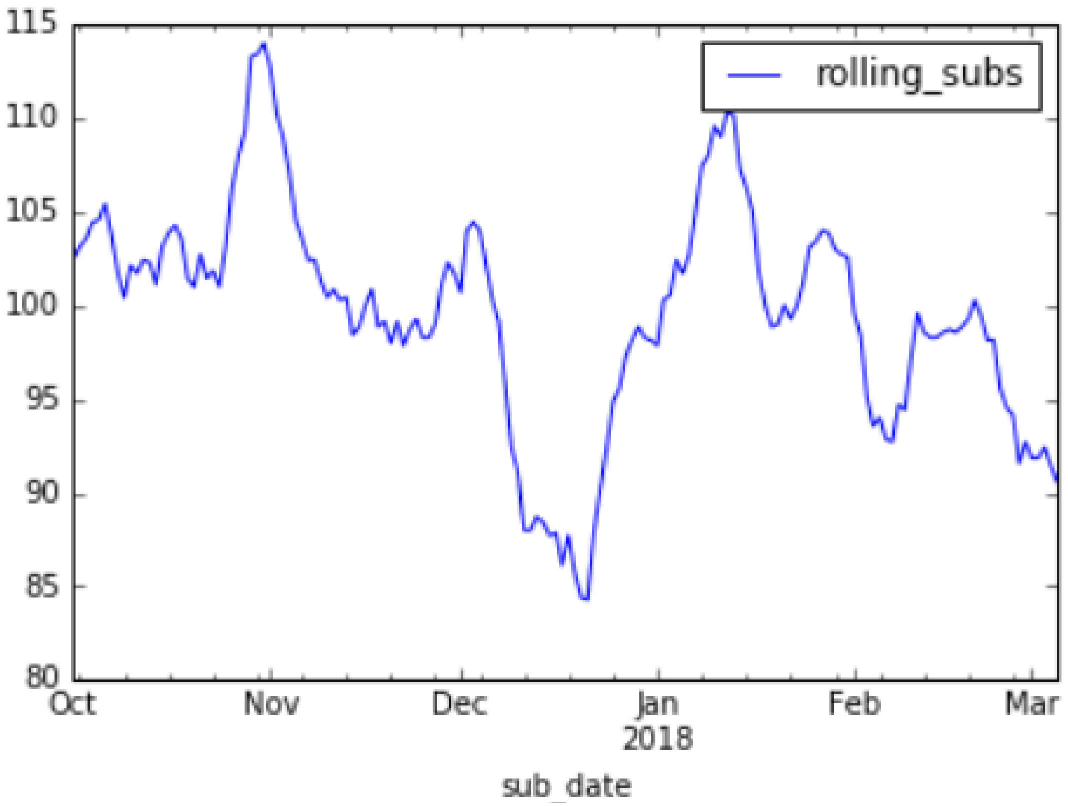
```
# calling rolling on the "subs" Series
rolling_subs =  usa_subscriptions.subs.rolling(
    # How many data points to average over
    window=7,
    # Specify to average backwards
    center=False
)
```

Smoothing our USA subscription data

```
# find the rolling average
usa_subscriptions['rolling_subs']
            = rolling_subs.mean()
usa_subscriptions.tail()
```

```
sub_date     subs        rolling_subs
2018-03-14   89          94.714286
2018-03-15   96          95.428571
2018-03-16   102         96.142857
```

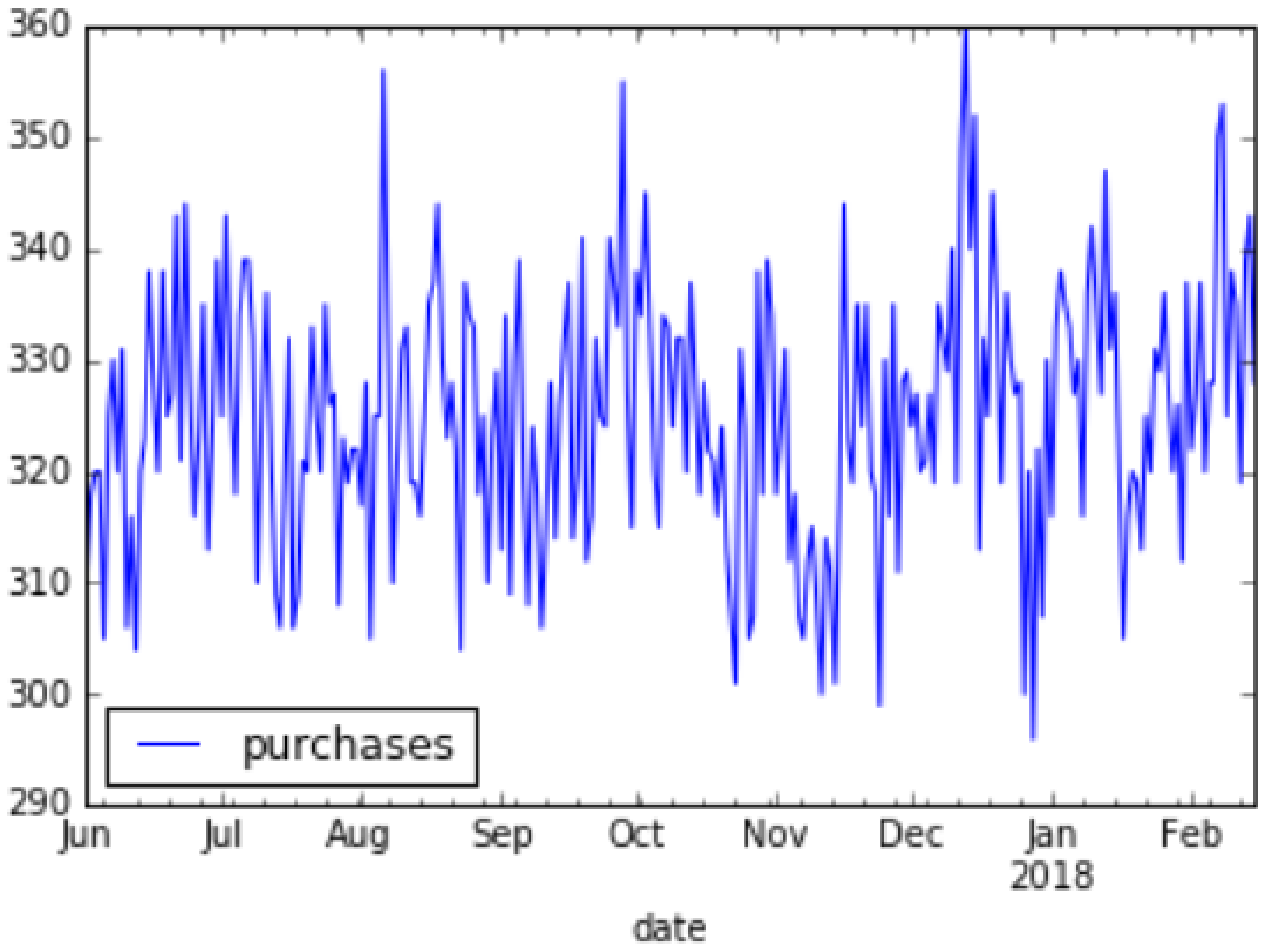
- `.rolling` like `groupby` specifies a grouping of data points
- We still need to calculate a summary over this group (e.g. `.mean()`)



Noisy data - Highest SKU purchases by date

- **Noisy Data:** data with high variation over time

```
# Load a dataset of our highest sku purchases
high_sku_purchases = pd.read_csv(
    'high_sku_purchases.csv',
    parse_dates=True,
    infer_datetime_format=True
)

# Plot the count of purchases by day of purchase
high_sku_purchases.plot(x='date', y='purchases')
plt.show()
```



Smoothing with an exponential moving average

- **Exponential Moving Average**: Weighted moving (rolling) average
  - Weights more recent items in the window more
  - Applies weights according to an exponential distribution
  - Averages back to a central trend without masking any recent movements

Smoothed purchases by date

- `.ewm()` : exponential weighting function
- `span` : Window to apply weights over

```
# Calculate the exp. avg. over our high sku
#  purchase count
exp_mean = high_sku_purchases.purchases.ewm(
    span=30)
```

```
# Find the weighted mean over this period
high_sku_purchases['exp_mean'] = exp_mean.mean()
```

High Sku Purchase Data

Summary - Data Smoothing Techniques

- **Trailing Average**:
  - Smooths seasonality by averaging over the periodicity
- **Exponential Moving Average**:
  - Reveals trends by pulling towards the central tendency
  - Weights the more recent values relative to the window more heavily
- You can use `.rolling()` and `.ewm()` for many more methods of smoothing

Let's practice!

CUSTOMER ANALYTICS AND A/B TESTING IN PYTHON

Events and releases

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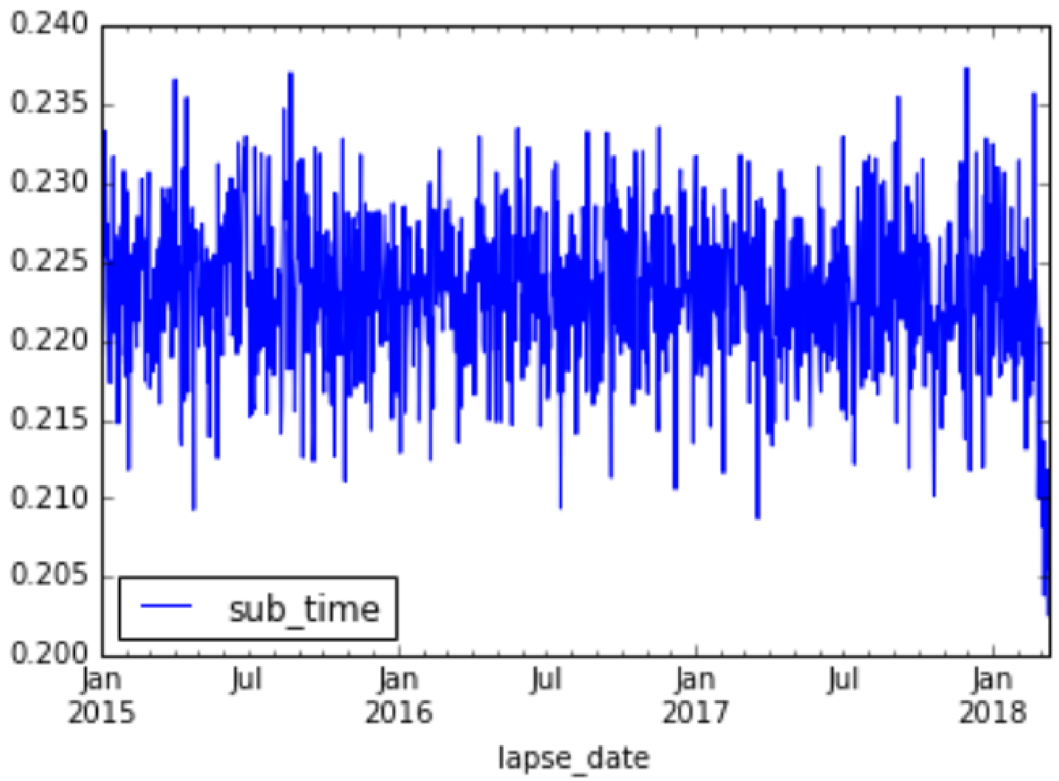
Exploratory analysis - issues in our ecosystem

Visualizing the drop in conversion rate (3 Years)

```
import pandas as pd
import matplotlib.pyplot as plt

# Remove users who lapsed within the past week
conv_sub_data = sub_data_demo[
    sub_data_demo.lapse_date <= max_lapse_date]

# Calculate the week one conversion rate by lapse
sub_time = (conv_sub_data.subscription_date -
    conv_sub_data.lapse_date).dt.days
conv_sub_data['sub_time'] = sub_time

conversion_data = conv_sub_data.groupby(
    by=['lapse_date'], as_index=False
).agg({'sub_time': [gc7]})
```

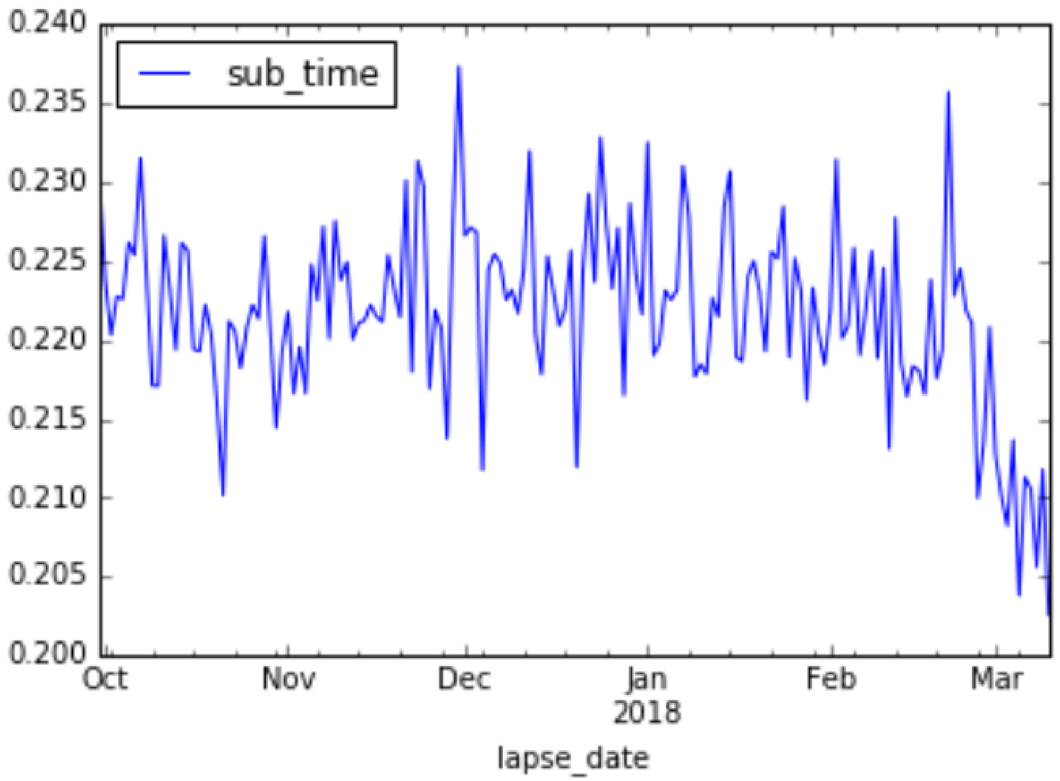
```
# Plot our conversion rate over time
conversion_data.plot()
plt.show()
```



Visualizing the drop in conversion rate (6 Months)

```
# Find the date boundries to limit our data by
current_date = pd.to_datetime('2018-03-17')

# 6 * 28 to reprsent the past 6 months
start_date = current_date - timedelta(days=(6*28

# A mask for our conversion rate data
conv_filter = (
    conversion_data.lapse_date >= start_date) &
    (conversion_data.lapse_date <= current_date)
)

# Filter our conversion rate data
con_data_filt = conversion_data[conv_filter]
```

```
conv_data_filt.plot(x='lapse_date', y='sub_time'
plt.show()
```



Investigating the conversion rate drop

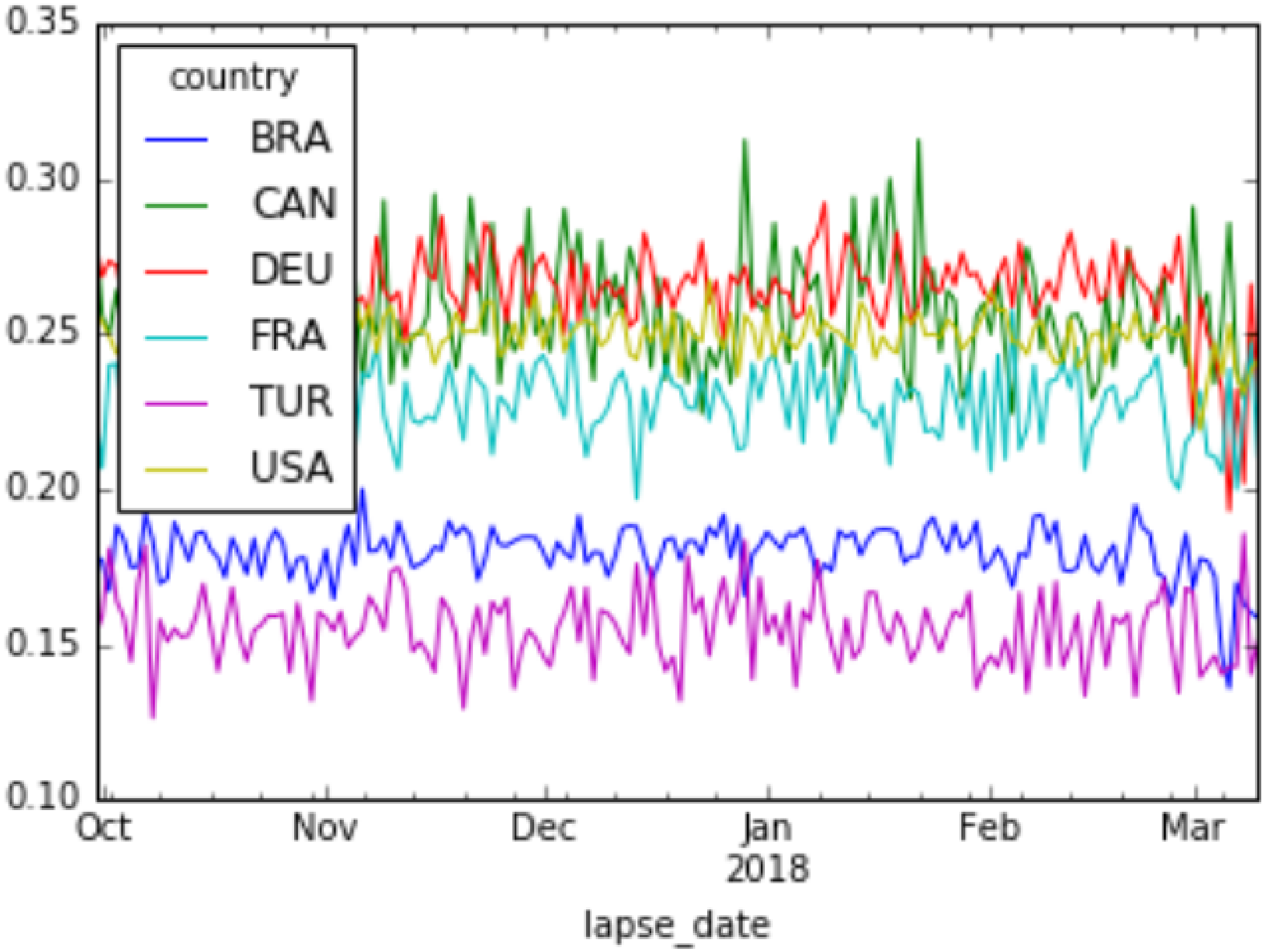
- Is this drop impacting all users or just a specific cohort
- This could provide clues on what the issue may be
- Ecosystems within our data
  - Distinct countries
  - Specific device (Android or iOS)

Splitting our data by country and device

```
# After filtering and calculating daily conversion...

# Pivot the results to have one colum per country
conv_data_cntry = pd.pivot_table(
    conv_data_cntry, values=['sub_time'],
    columns=['country'], index=['lapse_date'],fill_value=0
)

...

# Pivot the results to have one colum per device
conv_data_dev = pd.pivot_table(
    conv_data_dev, values=['sub_time'],
    columns=['device'], index=['lapse_date'],fill_value=0
)
```

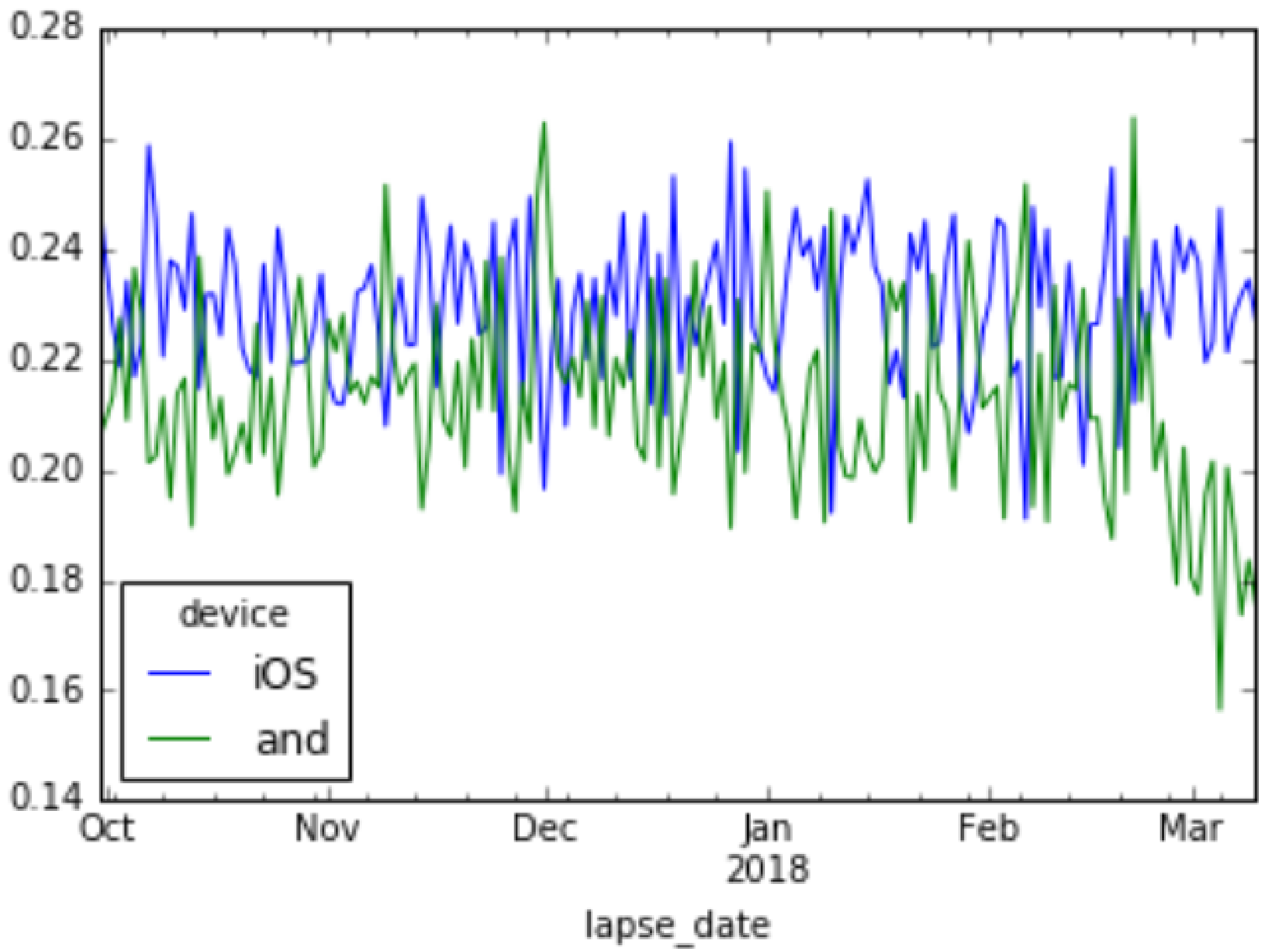
Breaking out by Country

- All countries experience the drop
- It is most pronounced in Brazil & Turkey
    - Our two most android heavy countries



Breaking out by Device

- The drop only appears on Android devices



Annotating datasets

- `events` : Holidays and events impacting user behavior

```
events = pd.read_csv('events.csv')
```

- `releases` : iOS and Android software releases

```
releases = pd.read_csv('releases.csv')
releases.head()
```

```
Date              Event
2018-03-14          iOS Release
2018-03-03          Android Release
2018-01-13          iOS Release
2018-01-15          Android Release
```

Plotting annotations - events

- `plt.axvline()` : Plots vertical line at the x-intercept
  - `color` : Specify the color of the plotted line
  - `linestyle` : The type of line to plot

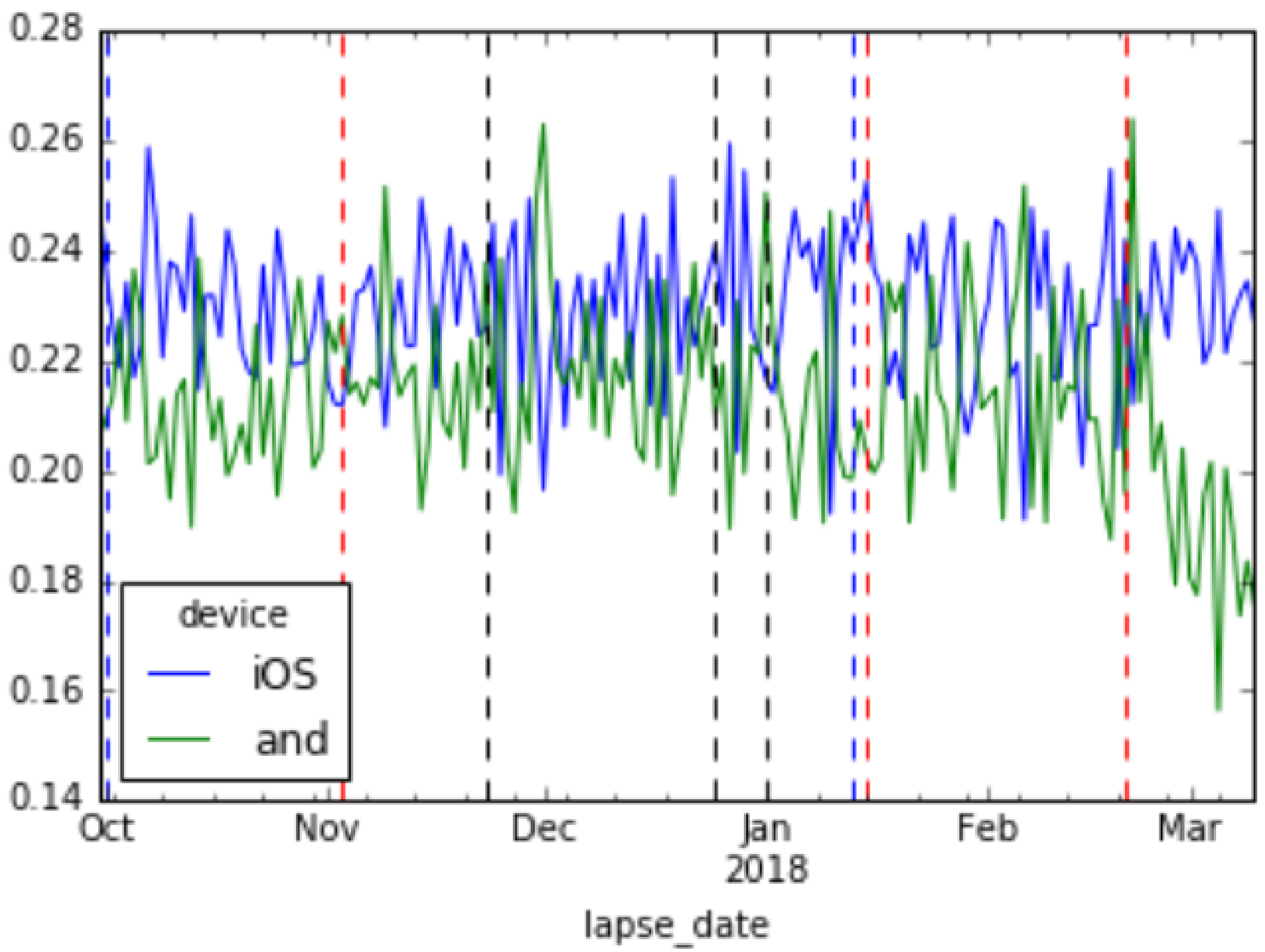
```
# Plot the conversion rate trend per device
conv_data_dev.plot(
    x=['lapse_date'], y=['iOS', 'and']
)

# Iterate through the events and plot each one
events.Date = pd.to_datetime(events.Date)
for row in events.iterrows():
    tmp = row[1]
    plt.axvline(
        x=tmp.Date, color='k', linestyle='--'
    )
```

Plotting annotations - releases

```
# Iterate through the releases and plot each one
releases.Date = pd.to_datetime(releases.Date)
for row in releases.iterrows():
    tmp = row[1]
    # plot iOS releases as a blue lines
    if tmp.Event == 'iOS Release':
        plt.axvline(x=tmp.Date, color='b', linestyle='--')

    # plot Android releases as red lines
    else:
        plt.axvline(x=tmp.Date, color='r', linestyle='--')
plt.show()
```

Annotated conversion rate graphs

- Android release in Feb/Mar aligns with our dip in conversion rate
- This release may contain a bug impacting the conversion rate!



Power and limitations of exploratory analysis

- Visualize data over time to uncover hidden trends
  - While useful it has its limitations
- To truly explore relationships in data we need A/B testing

Let's practice!

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