Sample Python Data Projects

SEO, Machine Learning, and Data Analysis

Internal Linking

Check every page for internal linking opportunities based on keyword.

sourceurl

https://www.trainerroad.com/blog/three-new-wor... sweet spot intervals

https://www.trainerroad.com/blog/an-update-on-...

https://www.trainerroad.com/blog/three-new-wor...

https://www.trainerroad.com/blog/three-new-wor...

4 https://www.trainerroad.com/blog/ask-chad-cade...

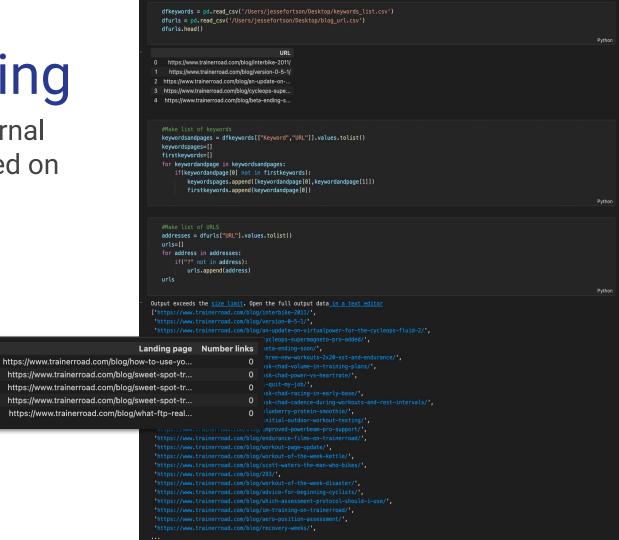
Search query

sweet spot training

power curve

spot training

threshold power



Keyword Cannibalization

Use the Google Search Console API to identify keyword cannibalisation across pages.

		unique pages	total clicks	total impressions	avg ctr	avg_position				
	query	adao_pagoo			<u>s_</u>	arg_position				
	ftp cycling	4	162	8358	9.965000	4.545000				
	how to increase ftp		35	357	38.827500	2.460000				
	ftp test		25	4272	4.785000	6.830000				
when to do an ftp test					46.296667	2.223333				
what does ftp stand for in cycling				323	11.726667	6.463333				
	ftp vs vo2 max		34	96	49.476667	1.103333				
what is ftp cycling			32	3543	33.953333	6.783333				
trainer road strength training					28.573333	2.810000				
sweet spot ftp			18	254	20.990000	3.826667				
how to improve ftp			33		43.900000	2.820000				
<pre>df[df['query']=='ftp test'].sort values(by='impressions', ascending=False).head(20)</pre>										
	query					page	clicks	impressions	ctr	position
945	ftp test		https://www.trainerroad.com/blog/ftp-assessment-tips/					3059	0.46	3.93
2667	2667 ftp test https://www.trainerroad.com/blog/what-ftp-really-means-to-cyclists/							1121	0.54	11.06
12789	ftp test https://www.trai	t https://www.trainerroad.com/blog/new-ramp-test-makes-ftp-testing-more-efficient-and-less-stressful/						68	1.47	10.25
4056	4056 ftp test https://www.trainerroad.com/blog/is-my-ftp-too-low/							24	16.67	2.08

```
def query(service, site url, payload):
       """Run a guery on the Google Search Console API and return a dataframe of results.
          service (object): Service object from connect()
          site url (string): URL of Google Search Console property
          payload (dict): API query payload dictionary
          df (dataframe): Pandas dataframe containing requested data.
      response = service.searchanalytics().query(siteUrl=site_url, body=payload).execute()
      results = []
       for row in response['rows']:
          data = \{\}
          for i in range(len(payload['dimensions']));
              data[payload['dimensions'][i]] = row['keys'][i]
          data['clicks'] = row['clicks']
          data['impressions'] = row['impressions']
          data['ctr'] = round(row['ctr'] * 100. 2)
          data['position'] = round(row['position'], 2)
          results.append(data)
      return pd.DataFrame.from_dict(results)
  payload = {
       'startDate': "2022-02-01",
       'endDate': "2022-03-01".
       'dimensions': ["query", "page", "date"],
       'rowLimit': 20000,
       'startRow': 0
  site_url =
  df = query(service, site_url, payload)
  df.head()
                                                  clicks impressions
       query
                                                                         ctr position
0 trainerroad https://www.trainerroad.com/ 2022-02-09
                                                                 1084 59.41
                                                                 1061 59.19
1 trainerroad https://www.trainerroad.com/ 2022-02-10
                                                                1007 60.38
2 trainerroad https://www.trainerroad.com/ 2022-02-08
```

1028 58.17

988 59.82

3 trainerroad https://www.trainerroad.com/ 2022-02-01

4 trainerroad https://www.trainerroad.com/ 2022-02-15

Google Analytics Anomaly Detection

Using the Google Analytics API to to detect a wide range of anomaly types.

```
#Change c=3.0 to increase the previous TS values, lowering increases sensativity

persist_ad = PersistAD(c=3, side='negative')
anomalies = persist_ad.fit_detect(s)

chart = plot(s,
    anomaly=anomalies,
    ts_linewidth=1,
    ts_markersize=3,
    anomaly_markersize=5,
    anomaly_color='red',
    anomaly_tag='marker')

2000

15000

15000

15000

20000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

15000

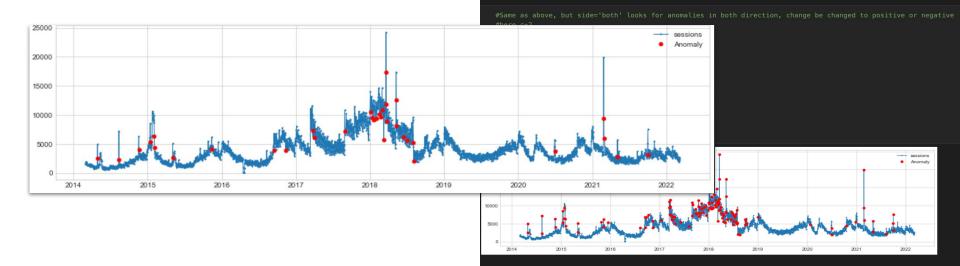
15000

15000

15000

15
```

#Uses a double rolling aggregate model and find anomolaies from previous time series.



Forecasting Sales with Machine Learning

