ml-visualization-with-yellowbrick

February 6, 2022

1 Machine Learning Kepler Exoplanet candidates

1.1 Data

This notebook uses the Kepler space observations dataset.

[1]:
```python
import yellowbrick as yb
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np

pd.set_option('max_columns', None)

df = pd.read_csv("cumulative.csv")

X = (df.iloc[:, 5:].assign(koi_pdisposition=(df.koi_pdisposition ==␣
↪"CANDIDATE").astype(int)).drop(columns=['koi_tce_delivname']))
y = df.koi_disposition == "CONFIRMED"

df.head()
```

[1]:
```
   rowid     kepid kepoi_name   kepler_name koi_disposition koi_pdisposition  \
0      1  10797460  K00752.01  Kepler-227 b       CONFIRMED        CANDIDATE
1      2  10797460  K00752.02  Kepler-227 c       CONFIRMED        CANDIDATE
2      3  10811496  K00753.01           NaN  FALSE POSITIVE   FALSE POSITIVE
3      4  10848459  K00754.01           NaN  FALSE POSITIVE   FALSE POSITIVE
4      5  10854555  K00755.01  Kepler-664 b       CONFIRMED        CANDIDATE

   koi_score  koi_fpflag_nt  koi_fpflag_ss  koi_fpflag_co  koi_fpflag_ec  \
0      1.000              0              0              0              0
1      0.969              0              0              0              0
2      0.000              0              1              0              0
3      0.000              0              1              0              0
4      1.000              0              0              0              0

   koi_period  koi_period_err1  koi_period_err2  koi_time0bk  \
0    9.488036      2.775000e-05    -2.775000e-05   170.538750
```

1	54.418383	2.479000e-04	-2.479000e-04	162.513840
2	19.899140	1.494000e-05	-1.494000e-05	175.850252
3	1.736952	2.630000e-07	-2.630000e-07	170.307565
4	2.525592	3.761000e-06	-3.761000e-06	171.595550

	koi_time0bk_err1	koi_time0bk_err2	koi_impact	koi_impact_err1	\
0	0.002160	-0.002160	0.146	0.318	
1	0.003520	-0.003520	0.586	0.059	
2	0.000581	-0.000581	0.969	5.126	
3	0.000115	-0.000115	1.276	0.115	
4	0.001130	-0.001130	0.701	0.235	

	koi_impact_err2	koi_duration	koi_duration_err1	koi_duration_err2	\
0	-0.146	2.95750	0.08190	-0.08190	
1	-0.443	4.50700	0.11600	-0.11600	
2	-0.077	1.78220	0.03410	-0.03410	
3	-0.092	2.40641	0.00537	-0.00537	
4	-0.478	1.65450	0.04200	-0.04200	

	koi_depth	koi_depth_err1	koi_depth_err2	koi_prad	koi_prad_err1	\
0	615.8	19.5	-19.5	2.26	0.26	
1	874.8	35.5	-35.5	2.83	0.32	
2	10829.0	171.0	-171.0	14.60	3.92	
3	8079.2	12.8	-12.8	33.46	8.50	
4	603.3	16.9	-16.9	2.75	0.88	

	koi_prad_err2	koi_teq	koi_teq_err1	koi_teq_err2	koi_insol	\
0	-0.15	793.0	NaN	NaN	93.59	
1	-0.19	443.0	NaN	NaN	9.11	
2	-1.31	638.0	NaN	NaN	39.30	
3	-2.83	1395.0	NaN	NaN	891.96	
4	-0.35	1406.0	NaN	NaN	926.16	

	koi_insol_err1	koi_insol_err2	koi_model_snr	koi_tce_plnt_num	\
0	29.45	-16.65	35.8	1.0	
1	2.87	-1.62	25.8	2.0	
2	31.04	-10.49	76.3	1.0	
3	668.95	-230.35	505.6	1.0	
4	874.33	-314.24	40.9	1.0	

	koi_tce_delivname	koi_steff	koi_steff_err1	koi_steff_err2	koi_slogg	\
0	q1_q17_dr25_tce	5455.0	81.0	-81.0	4.467	
1	q1_q17_dr25_tce	5455.0	81.0	-81.0	4.467	
2	q1_q17_dr25_tce	5853.0	158.0	-176.0	4.544	
3	q1_q17_dr25_tce	5805.0	157.0	-174.0	4.564	
4	q1_q17_dr25_tce	6031.0	169.0	-211.0	4.438	

```
   koi_slogg_err1  koi_slogg_err2  koi_srad  koi_srad_err1  koi_srad_err2  \
0           0.064          -0.096     0.927          0.105         -0.061
1           0.064          -0.096     0.927          0.105         -0.061
2           0.044          -0.176     0.868          0.233         -0.078
3           0.053          -0.168     0.791          0.201         -0.067
4           0.070          -0.210     1.046          0.334         -0.133

          ra        dec  koi_kepmag
0  291.93423  48.141651      15.347
1  291.93423  48.141651      15.347
2  297.00482  48.134129      15.436
3  285.53461  48.285210      15.597
4  288.75488  48.226200      15.509
```

1.2 Visualizations

1.2.1 Rank1D

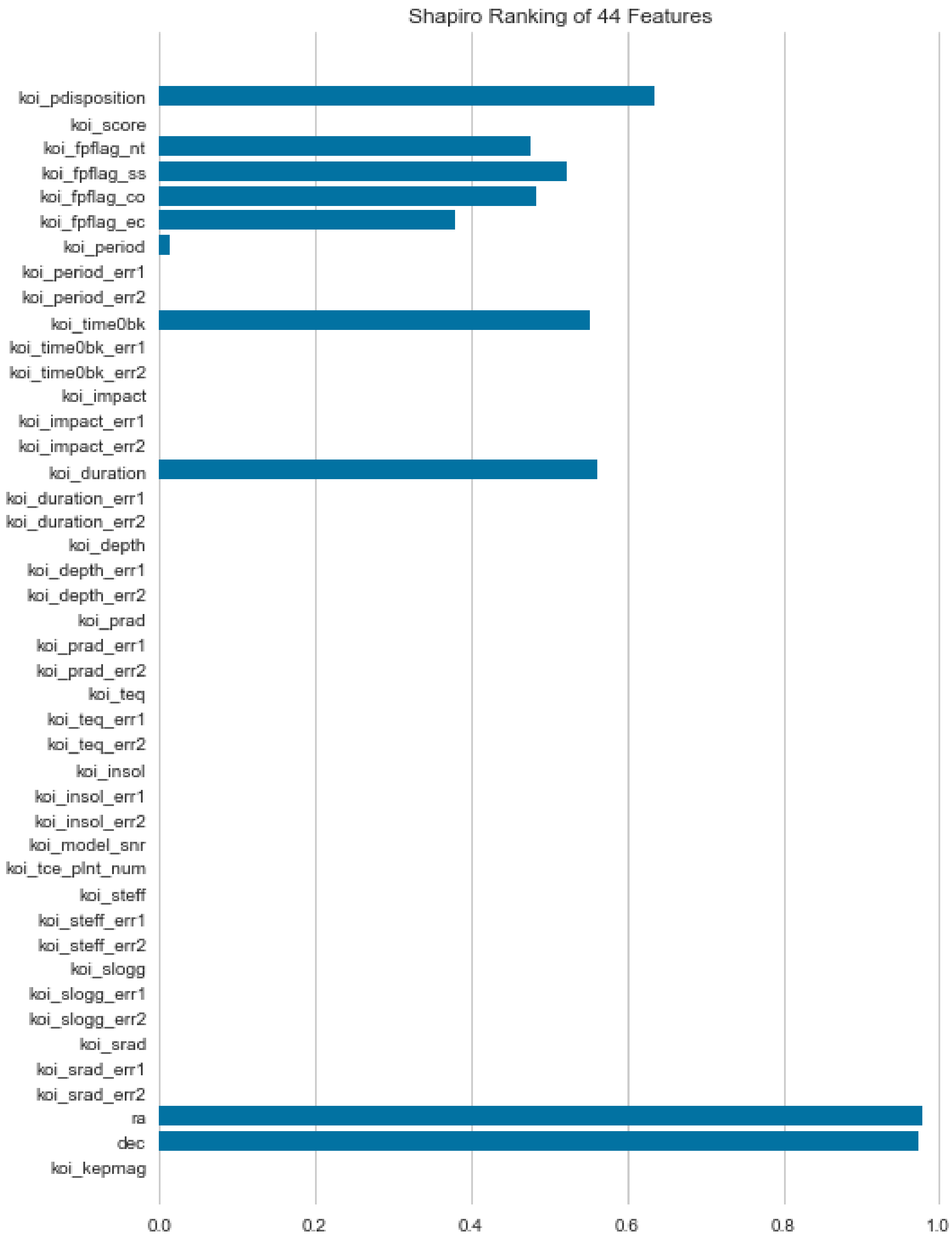
This plots a simple bar chart in one dimension ranking the data according to some statistic, hence the name. The name is a misnomer for now, however, as though the method provides an `algorithm` field the only algorithm that works at the moment is the Shapiro-Wilk test, a statistical test (with a confidence score on the $[0, 1]$ scale) of whether or not the given feature is normally distributed. The Shapiro-Wilk is a useful tool for visualizations because it lets you test normality of variables using a single test statistic, e.g. without relying on a huge list of plots. Much less cumbersome. For more on the test, the Wikipedia article is informative.

Here's what you get:

[2]:
```python
from yellowbrick.features import Rank1D

fig, ax = plt.subplots(1, figsize=(8, 12))
vzr = Rank1D(ax=ax)
vzr.fit(X, y)
vzr.transform(X)
sns.despine(left=True, bottom=True)
vzr.poof()
```

```
C:\Users\Richard\anaconda3\lib\site-packages\scipy\stats\morestats.py:1681:
UserWarning: p-value may not be accurate for N > 5000.
  warnings.warn("p-value may not be accurate for N > 5000.")
```



[2]: <AxesSubplot:title={'center':'Shapiro Ranking of 44 Features'}>

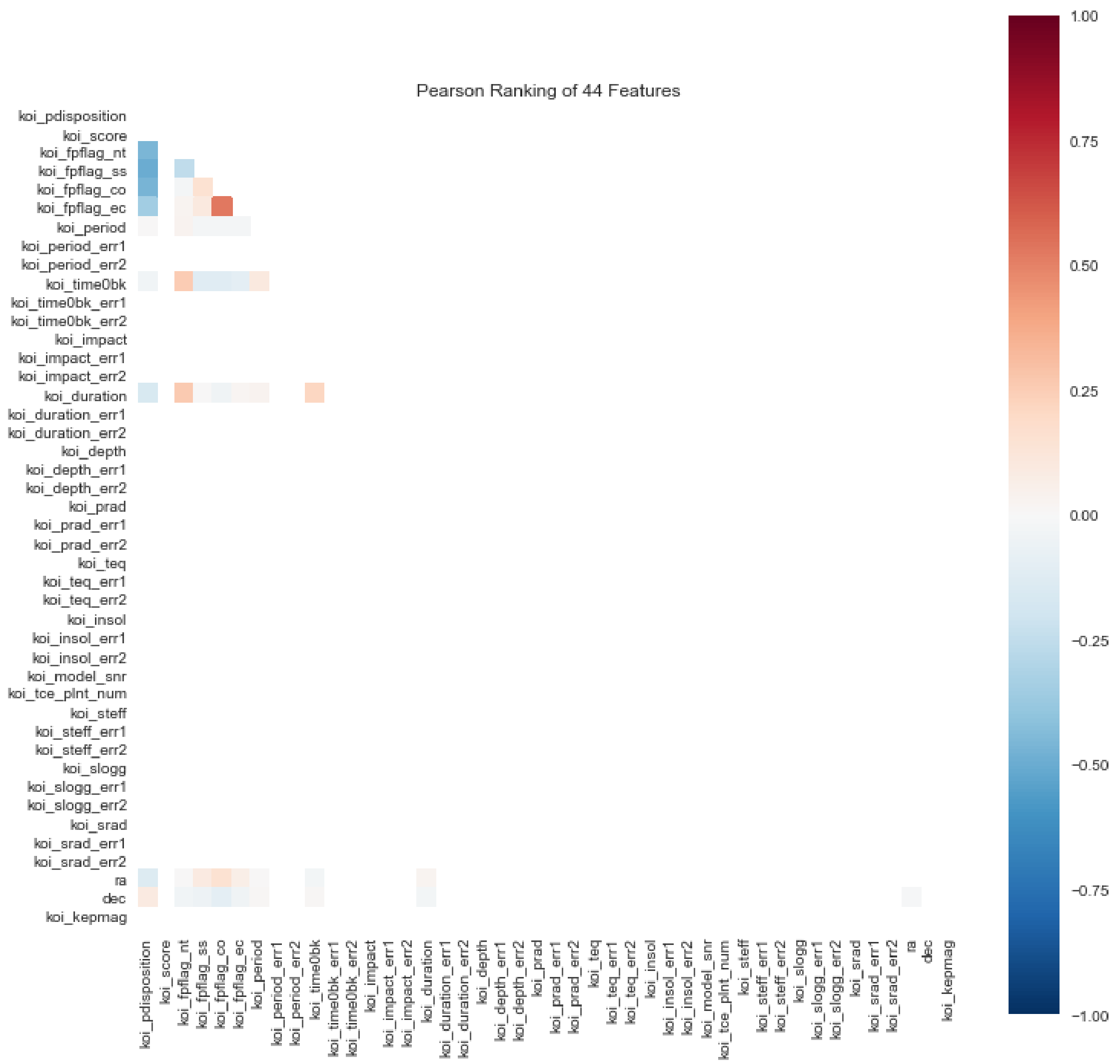
This is the output of a statistical test, but since we're not making any decisions based on it there's no need to choose a specific level of significance (p value). You can see that `ra` and `dec` are very normally distributed ($p = 0.05$). The rest of the values are not normally distributed. Note that those flag values, which may only be 0 or 1, are scoring between 0.5 and 0.6 according to this metric! Semi-interesting.

1.3 Rank2D

Rank2D implements a `seaborn` heatmap with some good defaults. Where `Rank1D` relies on one-dimensional metrics, `Rank2D` provides a facility for two-dimensional metrics, e.g. things like correlation, covariance, and so on.

[3]:
```
from yellowbrick.features import Rank2D

fig, ax = plt.subplots(1, figsize=(12, 12))
vzr = Rank2D(ax=ax)
vzr.fit(X, y)
vzr.transform(X)
sns.despine(left=True, bottom=True)
vzr.poof()
```



```
[3]: <AxesSubplot:title={'center':'Pearson Ranking of 44 Features'}>
```

Again the API is super-limiting, with only `covariance` and `pearson` options. There are lots more useful metrics that could be implemented; Spearmen's correlation, for example

1.4 Parallel Coordinates

Parallel coordinates are a lovely plot type. Given an input of normalized data, parallel coordinate plotting will lay out the feature space and plot out where each point falls on it.

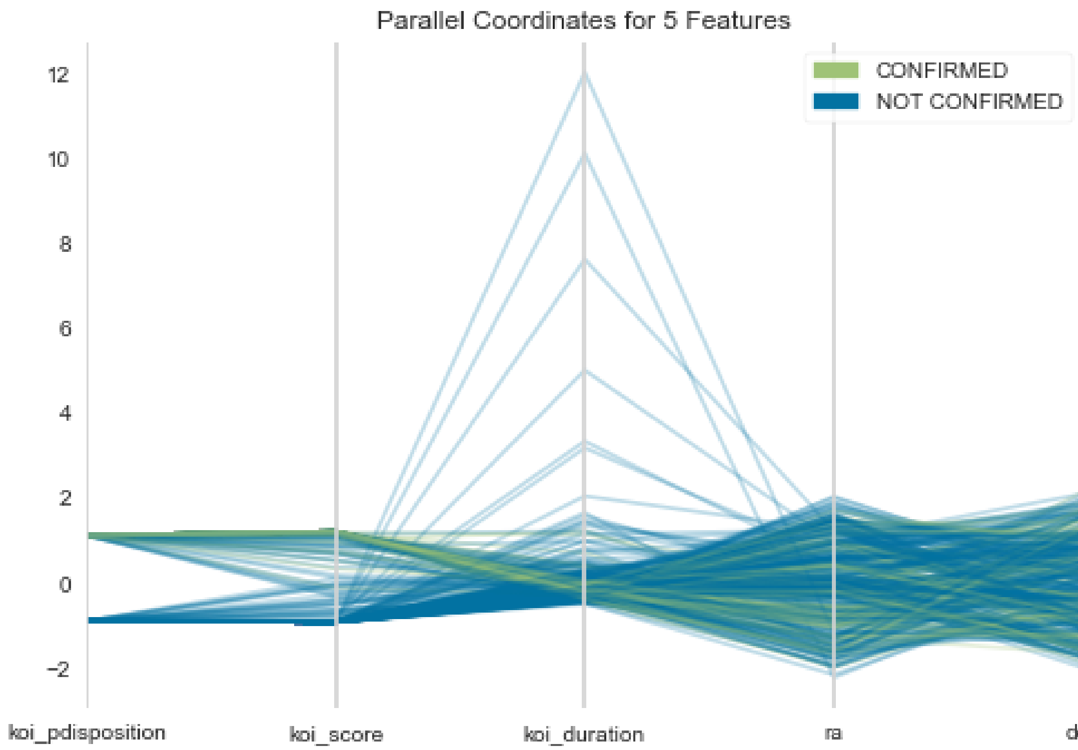
```
[4]: from yellowbrick.features import ParallelCoordinates
from sklearn.preprocessing import StandardScaler

# Select a handful of relevant columns and drop nulls.
np.random.seed()
cols = ['koi_pdisposition', 'koi_score', 'koi_duration', 'ra', 'dec']
X_sample = X.sample(500).loc[:, cols].dropna()
y_sample = y.iloc[X_sample.index.values].reset_index(drop=True)

# Normalize all of the fields.
trans = StandardScaler()
trans.fit(X_sample)
X_sample = pd.DataFrame(trans.transform(X_sample), columns=cols)

# Fit the chart.
# fig, ax = plt.subplots(1, figsize=(12, 6))
kwargs = {'vlines_kwds': {'color': 'lightgray'}}
vzr = ParallelCoordinates(classes=['NOT CONFIRMED', 'CONFIRMED'], **kwargs)  #␣
↪ax=ax
vzr.fit(X_sample, y_sample)
vzr.transform(X_sample)
sns.despine(left=True, bottom=True)

# Display.
vzr.poof()
```



[4]: <AxesSubplot:title={'center':'Parallel Coordinates for 5 Features'}>

We see a few different interesting effects here. For one there's a long push of outliers of observation durations, all of which correspond with observations that were `NOT CONFIRMED`. That seems significant. Also, we can see that the probability that Kepler assigns to planets that get `CONFIRMED` (`koi_score`) is quite high, but not always 100 percent (in interpreting this fact, recall that this feature is scaled to fall between $[-1, 1]$).

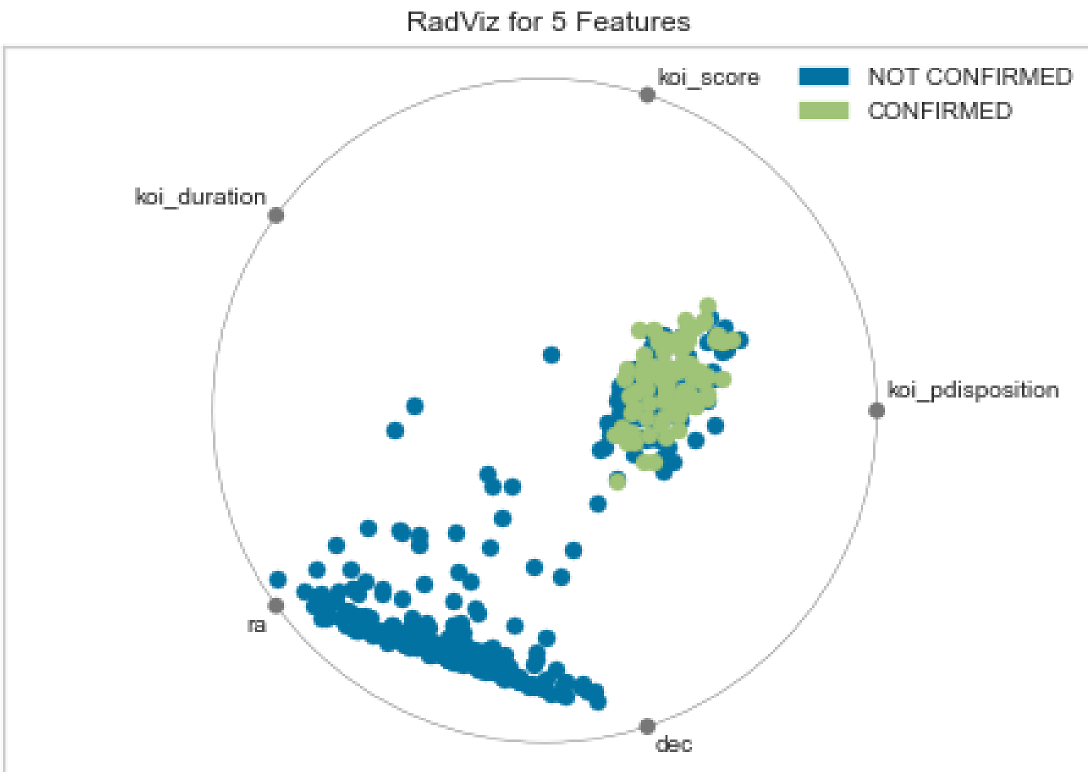
Parallel coordinates plots are overall a very useful chart type, though not one without weaknesses. It's great to have a neat interface to it like this. But it's worth pointing out that this plot type is just reimplementing a `pandas.plotting` built-in). Meanwhile another related albeit less interpretable `pandas.plotting` built-in, the Andrews curve, is missing.

1.4.1 RadViz

`RadViz` is another re-packaged `pandas.plotting` built-in. This visualization type lays out the features of the dataset in a circle, then plots the position of each point under consideration in that circle by pushing it towards the variables it loads heavily in. This is also sometimes called the "spring layout". It can be quite useful for visualizing distinguishabile attributes between class clusters; I find it to be a very understandable way of explaining which n variables a particular class loads heavily on, when n is greater than 2.

[5]:
```
from yellowbrick.features import RadViz
```

```
# fig, ax = plt.subplots(1, figsize=(12, 6))
# cmap = y_sample.map(lambda v: "steelblue" if v else "lightgray")
vzr = RadViz(classes=['NOT CONFIRMED', 'CONFIRMED'])
vzr.fit_transform(X_sample, y_sample)
vzr.poof()
```



[5]: <AxesSubplot:title={'center':'RadViz for 5 Features'}>

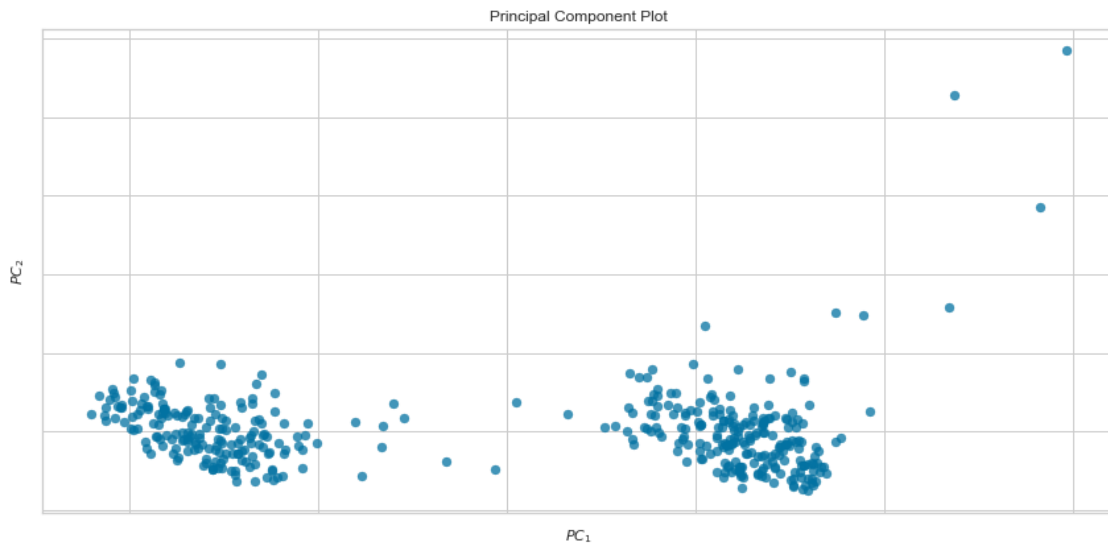
This chart only tells us that planets that got confirmed loaded heavily in the pre-disposition, which is something we probably already figured.

1.4.2 PCADecomposition

PCA, or Principal Components Analysis, is a dimensionality reduction technique which lets us drop the number of variables under consideration to some user-specified subset thereof. PCA works by finding the "natural directions" in a dataset, e.g. calculating new synthetic feature observations along the dataset axes that cover the most variance in the dataset, and hence, are the most "interesting". Note that PCA is an unsupervised algorithm that does not consider labels we assign to the data (e.g. classes).

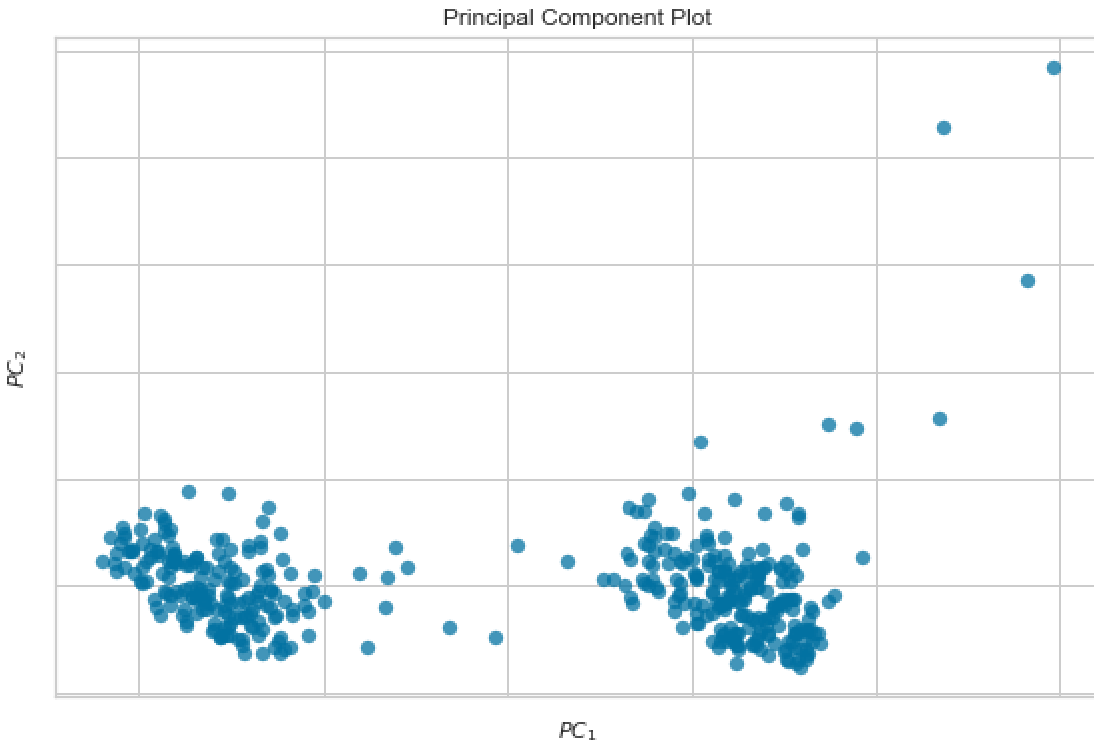
[19]:
```
from yellowbrick.features import PCADecomposition
```

```
fig, ax = plt.subplots(1, figsize=(12, 6))
cmap = y_sample.map(lambda v: "steelblue" if v else "lightgray")
vzr = PCADecomposition(color=cmap)
vzr.fit_transform(X_sample)
vzr.poof()
```



[19]: <AxesSubplot:title={'center':'Principal Component Plot'}, xlabel='PC_1', ylabel='PC_2'>

[16]:
```
from yellowbrick.features import PCADecomposition
vzr = PCADecomposition(proj_dim=3)
vzr.fit_transform(X_sample)
vzr.poof()
```



[16]: <AxesSubplot:title={'center':'Principal Component Plot'}, xlabel='PC_1', ylabel='PC_2'>

These 2-d and 3-d scatter plots are good for probing how difficult a classification or regression problem will be. Here we see that the observations naturally cluster into two groups, but that the relative distribution of the class of interest *within* that group doesn't differ between them. If we move on to examining what it is about the data that is creating these quite separable structures, we will make great gains in understanding what the underlying data describes.

There is more that can be done with PCA than this, though. This library needs more options!

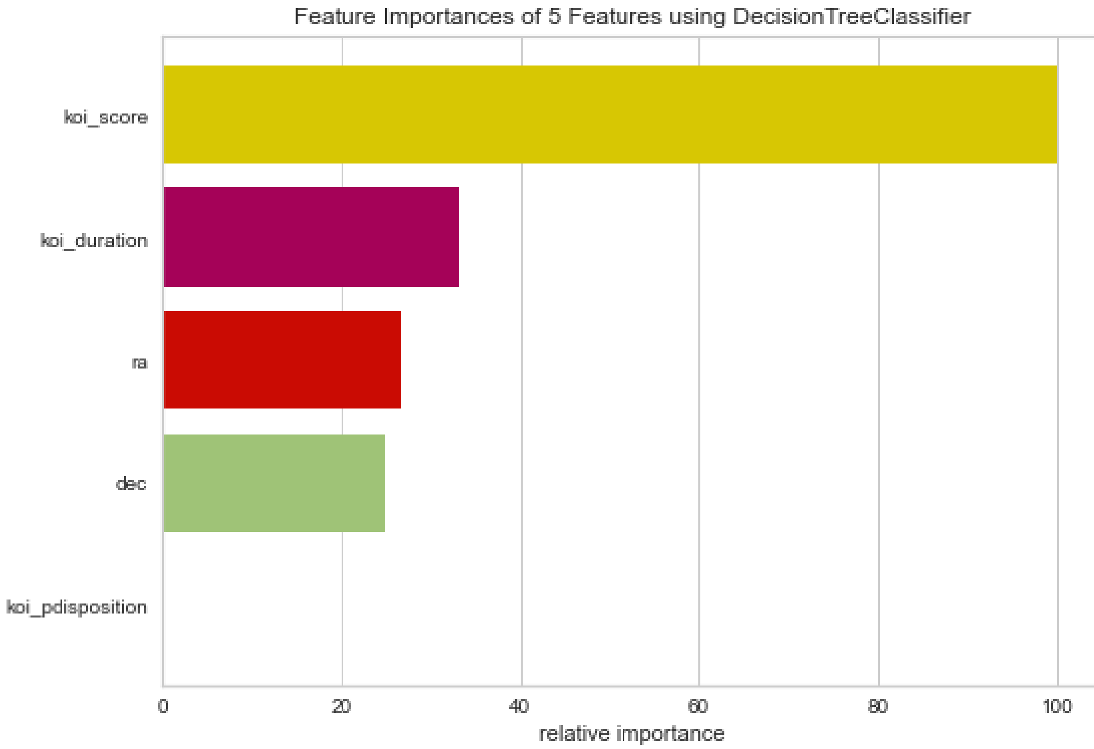
1.4.3 Feature Importances

Feature importance is the relative usefulness of a given feature for performing a classification or regression task. The `FeatureImportances` chart type takes advantage of the exploratory power of decision tree algorithms, which provide a `feature_importance_` result once fitted, to plot this information directly.

[17]:
```
from sklearn.tree import DecisionTreeClassifier
from yellowbrick.features import FeatureImportances

clf = DecisionTreeClassifier()
viz = FeatureImportances(clf)
viz.fit(X_sample, y_sample)
```

```
viz.poof()
```



[17]: <AxesSubplot:title={'center':'Feature Importances of 5 Features using DecisionTreeClassifier'}, xlabel='relative importance'>