4 Pre-Processing and Training Data

4.1 Contents

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4.2 Introduction

In preceding notebooks, performed preliminary assessments of data quality and refined the question to be answered. You found a small number of data values that gave clear choices about whether to replace values or drop a whole row. You determined that predicting the adult weekend ticket price was your primary aim. You threw away records with missing price data, but not before making the most of the other available data to look for any patterns between the states. You didn't see any and decided to treat all states equally; the state label didn't seem to be particularly useful.

In this notebook you'll start to build machine learning models. Before even starting with learning a machine learning model, however, start by considering how useful the mean value is as a predictor. This is more than just a pedagogical device. You never want to go to stakeholders with a machine learning model only to have the CEO point out that it performs worse than just guessing the average! Your first model is a baseline performance comparitor for any subsequent model. You then build up the process of efficiently and robustly creating and assessing models against it. The development we lay out may be little slower than in the real world, but this step of the capstone is definitely more than just instructional. It is good practice to build up an understanding that the machine learning pipelines you build work as expected. You can validate steps with your own functions for checking expected equivalence between, say, pandas and sklearn implementations.

4.3 Imports

In [1]:
```
import pandas as pd
import numpy as np
import os
import pickle
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn import __version__ as sklearn_version
from sklearn.decomposition import PCA
from sklearn.preprocessing import scale
from sklearn.model_selection import train_test_split, cross_validate, GridS
from sklearn.preprocessing import StandardScaler, MinMaxScaler
from sklearn.dummy import DummyRegressor
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import r2_score, mean_squared_error, mean_absolute_err
from sklearn.pipeline import make_pipeline
from sklearn.impute import SimpleImputer
from sklearn.feature_selection import SelectKBest, f_regression
import datetime
```

4.4 Load Data

In [3]:
```
path = "/Users/jasonzhou/Documents/GitHub/DataScienceGuidedCapstone"
os.chdir(path)
```

In [4]:
```
ski_data = pd.read_csv('data/ski_data_step3_features.csv')
ski_data.head().T
```

Out[4]:

	0	1	2	3	4
Name	Alyeska Resort	Eaglecrest Ski Area	Hilltop Ski Area	Arizona Snowbowl	Sunrise Park Resort
Region	Alaska	Alaska	Alaska	Arizona	Arizona
state	Alaska	Alaska	Alaska	Arizona	Arizona
summit_elev	3939	2600	2090	11500	11100
vertical_drop	2500	1540	294	2300	1800
base_elev	250	1200	1796	9200	9200
trams	1	0	0	0	0
fastSixes	0	0	0	1	0
fastQuads	2	0	0	0	1
quad	2	0	0	2	2
triple	0	0	1	2	3

4.5 Extract Big Mountain Data

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Big Mountain is your resort. Separate it from the rest of the data to use later.

In [5]:
```
big_mountain = ski_data[ski_data.Name == 'Big Mountain Resort']
```

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In [6]:
```
big_mountain.T
```

Out[6]:

	124
Name	Big Mountain Resort
Region	Montana
state	Montana
summit_elev	6817
vertical_drop	2353
base_elev	4464
trams	0
fastSixes	0
fastQuads	3
quad	2
triple	6
double	0
surface	3
total_chairs	14
Runs	105
TerrainParks	4
LongestRun_mi	3.3
SkiableTerrain_ac	3000
Snow Making_ac	600
daysOpenLastYear	123
yearsOpen	72
averageSnowfall	333
AdultWeekend	81
projectedDaysOpen	123
NightSkiing_ac	600
resorts_per_state	12
resorts_per_100kcapita	1.12278
resorts_per_100ksq_mile	8.16104
resort_skiable_area_ac_state_ratio	0.140121
resort_days_open_state_ratio	0.129338
resort_terrain_park_state_ratio	0.148148
resort_night_skiing_state_ratio	0.84507
total_chairs_runs_ratio	0.133333

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	124
total_chairs_skiable_ratio	0.00466667
fastQuads_runs_ratio	0.0285714
fastQuads_skiable_ratio	0.001

In [7]:
```
ski_data.shape
```
Out[7]:
```
(277, 36)
```

In [8]:
```
ski_data = ski_data[ski_data.Name != 'Big Mountain Resort']
```

In [9]:
```
ski_data.shape
```
Out[9]:
```
(276, 36)
```

4.6 Train/Test Split

So far, you've treated ski resort data as a single entity. In machine learning, when you train your model on all of your data, you end up with no data set aside to evaluate model performance. You could keep making more and more complex models that fit the data better and better and not realise you were overfitting to that one set of samples. By partitioning the data into training and testing splits, without letting a model (or missing-value imputation) learn anything about the test split, you have a somewhat independent assessment of how your model might perform in the future. An often overlooked subtlety here is that people all too frequently use the test set to assess model performance *and then compare multiple models to pick the best*. This means their overall model selection process is fitting to one specific data set, now the test split. You could keep going, trying to get better and better performance on that one data set, but that's where cross-validation becomes especially useful. While training models, a test split is very useful as a final check on expected future performance.

What partition sizes would you have with a 70/30 train/test split?

In [10]:
```
len(ski_data) * .7, len(ski_data) * .3
```
Out[10]:
```
(193.2, 82.8)
```

In [11]:
```
X_train, X_test, y_train, y_test = train_test_split(ski_data.drop(columns='
                                                    ski_data.AdultWeekend,
                                                    random_state=47)
```

In [12]:
```
X_train.shape, X_test.shape
```
Out[12]:
```
((193, 35), (83, 35))
```

In [13]:
```
y_train.shape, y_test.shape
```
Out[13]:
```
((193,), (83,))
```

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In [15]:
```
X_train
```

Out[15]:

	Name	Region	state	summit_elev	vertical_drop	base_elev	trams	fastSi
108	Powder Ridge Ski Area	Minnesota	Minnesota	790	300	500	0	
96	The Homestead	Michigan	Michigan	900	320	580	0	
189	Beech Mountain Resort	North Carolina	North Carolina	5506	830	4675	0	
232	Solitude Mountain Resort	Salt Lake City	Utah	10488	2494	7994	0	
1	Eaglecrest Ski Area	Alaska	Alaska	2600	1540	1200	0	
...	...	...	...	...	...	...	...	
23	Monarch Mountain	Colorado	Colorado	11952	1162	10790	0	
180	Toggenburg Mountain	New York	New York	2000	700	1300	0	
72	Wachusett Mountain Ski Area	Massachusetts	Massachusetts	2006	1000	1006	0	
265	Nordic Mountain	Wisconsin	Wisconsin	1137	265	872	0	
136	King Pine	New Hampshire	New Hampshire	850	350	500	0	

193 rows × 35 columns

In [17]:
```
#Code task 1#
#Save the 'Name', 'state', and 'Region' columns from the train/test data in
#Then drop those columns from `X_train` and `X_test`. Use 'inplace=True'
names_list = ['Name', 'state', 'Region']
names_train = X_train[names_list]
names_test = X_test[names_list]
X_train.drop(columns=names_list, inplace=True)
X_test.drop(columns=names_list, inplace=True)
X_train.shape, X_test.shape
```

Out[17]: ((193, 32), (83, 32))

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In [19]:
```
#Code task 2#
#Check the `dtypes` attribute of `X_train` to verify all features are numer
X_train.dtypes
```

Out[19]:
```
summit_elev                             int64
vertical_drop                           int64
base_elev                               int64
trams                                   int64
fastSixes                               int64
fastQuads                               int64
quad                                    int64
triple                                  int64
double                                  int64
surface                                 int64
total_chairs                            int64
Runs                                  float64
TerrainParks                          float64
LongestRun_mi                         float64
SkiableTerrain_ac                     float64
Snow Making_ac                        float64
daysOpenLastYear                      float64
yearsOpen                             float64
averageSnowfall                       float64
projectedDaysOpen                     float64
NightSkiing_ac                        float64
resorts_per_state                       int64
resorts_per_100kcapita                float64
resorts_per_100ksq_mile               float64
resort_skiable_area_ac_state_ratio    float64
resort_days_open_state_ratio          float64
resort_terrain_park_state_ratio       float64
resort_night_skiing_state_ratio       float64
total_chairs_runs_ratio               float64
total_chairs_skiable_ratio            float64
fastQuads_runs_ratio                  float64
fastQuads_skiable_ratio               float64
dtype: object
```

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In [18]:
```
#Code task 3#
#Repeat this check for the test split in `X_test`
X_test.dtypes
```

Out[18]:
```
summit_elev                            int64
vertical_drop                          int64
base_elev                              int64
trams                                  int64
fastSixes                              int64
fastQuads                              int64
quad                                   int64
triple                                 int64
double                                 int64
surface                                int64
total_chairs                           int64
Runs                                 float64
TerrainParks                         float64
LongestRun_mi                        float64
SkiableTerrain_ac                    float64
Snow Making_ac                       float64
daysOpenLastYear                     float64
yearsOpen                            float64
averageSnowfall                      float64
projectedDaysOpen                    float64
NightSkiing_ac                       float64
resorts_per_state                      int64
resorts_per_100kcapita               float64
resorts_per_100ksq_mile              float64
resort_skiable_area_ac_state_ratio   float64
resort_days_open_state_ratio         float64
resort_terrain_park_state_ratio      float64
resort_night_skiing_state_ratio      float64
total_chairs_runs_ratio              float64
total_chairs_skiable_ratio           float64
fastQuads_runs_ratio                 float64
fastQuads_skiable_ratio              float64
dtype: object
```

You have only numeric features in your X now!

4.7 Initial Not-Even-A-Model

A good place to start is to see how good the mean is as a predictor. In other words, what if you simply say your best guess is the average price?

In [20]:
```
#Code task 4#
#Calculate the mean of `y_train`
train_mean = y_train.mean()
train_mean
```

Out[20]:
```
63.811088082901556
```

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`sklearn`'s `DummyRegressor` easily does this:

In [22]:
```
#Code task 5#
#Fit the dummy regressor on the training data
#Hint, call its `.fit()` method with `X_train` and `y_train` as arguments
#Then print the object's `constant_` attribute and verify it's the same as
dumb_reg = DummyRegressor(strategy='mean')
dumb_reg.fit(X_train, y_train)
dumb_reg.constant_
```

Out[22]:
```
array([[63.81108808]])
```

How good is this? How closely does this match, or explain, the actual values? There are many ways of assessing how good one set of values agrees with another, which brings us to the subject of metrics.

4.7.1 Metrics

4.7.1.1 R-squared, or coefficient of determination

One measure is R^2, the [coefficient of determination (https://en.wikipedia.org/wiki/Coefficient_of_determination)](https://en.wikipedia.org/wiki/Coefficient_of_determination). This is a measure of the proportion of variance in the dependent variable (our ticket price) that is predicted by our "model". The linked Wikipedia articles gives a nice explanation of how negative values can arise. This is frequently a cause of confusion for newcomers who, reasonably, ask how can a squared value be negative?

Recall the mean can be denoted by $\bar{y}$, where

$$\bar{y} = \frac{1}{n}\sum_{i=1}^{n}y_i$$

and where y_i are the individual values of the dependent variable.

The total sum of squares (error), can be expressed as

$$SS_{tot} = \sum_i (y_i - \bar{y})^2$$

The above formula should be familiar as it's simply the variance without the denominator to scale (divide) by the sample size.

The residual sum of squares is similarly defined to be

$$SS_{res} = \sum_i (y_i - \hat{y})^2$$

where $\hat{y}$ are our predicted values for the depended variable.

The coefficient of determination, R^2, here is given by

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$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}}$$

Putting it into words, it's one minus the ratio of the residual variance to the original variance. Thus, the baseline model here, which always predicts $\bar{y}$, should give $R^2 = 0$. A model that perfectly predicts the observed values would have no residual error and so give $R^2 = 1$. Models that do worse than predicting the mean will have increased the sum of squares of residuals and so produce a negative R^2.

In [23]:
```
#Code task 6#
#Calculate the R^2 as defined above
def r_squared(y, ypred):
    """R-squared score.

    Calculate the R-squared, or coefficient of determination, of the input.

    Arguments:
    y -- the observed values
    ypred -- the predicted values
    """
    ybar = np.sum(y) / len(y) #yes, we could use np.mean(y)
    sum_sq_tot = np.sum((y - ybar)**2) #total sum of squares error
    sum_sq_res = np.sum((y - ypred)**2) #residual sum of squares error
    R2 = 1.0 - sum_sq_res / sum_sq_tot
    return R2
```

Make your predictions by creating an array of length the size of the training set with the single value of the mean.

In [24]:
```
y_tr_pred_ = train_mean * np.ones(len(y_train))
y_tr_pred_[:5]
```

Out[24]:
```
array([63.81108808, 63.81108808, 63.81108808, 63.81108808, 63.81108808])
```

Remember the `sklearn` dummy regressor?

In [25]:
```
y_tr_pred = dumb_reg.predict(X_train)
y_tr_pred[:5]
```

Out[25]:
```
array([63.81108808, 63.81108808, 63.81108808, 63.81108808, 63.81108808])
```

You can see that `DummyRegressor` produces exactly the same results and saves you having to mess about broadcasting the mean (or whichever other statistic we used - check out the [documentation (https://scikit-learn.org/stable/modules/generated/sklearn.dummy.DummyRegressor.html)](https://scikit-learn.org/stable/modules/generated/sklearn.dummy.DummyRegressor.html) to see what's available) to an array of the appropriate length. It also gives you an object with `fit()` and `predict()` methods as well so you can use them as conveniently as any other `sklearn` estimator.

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In [26]:
```
r_squared(y_train, y_tr_pred)
```

Out[26]:
```
0.0
```

Exactly as expected, if you use the average value as your prediction, you get an R^2 of zero *on our training set*. What if you use this "model" to predict unseen values from the test set? Remember, of course, that your "model" is trained on the training set; you still use the training set mean as your prediction.

Make your predictions by creating an array of length the size of the test set with the single value of the (training) mean.

In [27]:
```
y_te_pred = train_mean * np.ones(len(y_test))
r_squared(y_test, y_te_pred)
```

Out[27]:
```
-0.0031235200417913944
```

Generally, you can expect performance on a test set to be slightly worse than on the training set. As you are getting an R^2 of zero on the training set, there's nowhere to go but negative!

R^2 is a common metric, and interpretable in terms of the amount of variance explained, it's less appealing if you want an idea of how "close" your predictions are to the true values. Metrics that summarise the difference between predicted and actual values are *mean absolute error* and *mean squared error*.

4.7.1.2 Mean Absolute Error

This is very simply the average of the absolute errors:

$$MAE = \frac{1}{n}\sum_{i}^{n} |y_i - \hat{y}|$$

In [28]:
```
#Code task 7#
#Calculate the MAE as defined above
def mae(y, ypred):
    """Mean absolute error.

    Calculate the mean absolute error of the arguments

    Arguments:
    y -- the observed values
    ypred -- the predicted values
    """
    abs_error = np.abs(y - ypred)
    mae = np.mean(abs_error)
    return mae
```

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In [29]:
```
mae(y_train, y_tr_pred)
```
Out[29]:
```
17.923463717146785
```

In [30]:
```
mae(y_test, y_te_pred)
```
Out[30]:
```
19.136142081278486
```

Mean absolute error is arguably the most intuitive of all the metrics, this essentially tells you that, on average, you might expect to be off by around $19 if you guessed ticket price based on an average of known values.

4.7.1.3 Mean Squared Error

Another common metric (and an important one internally for optimizing machine learning models) is the mean squared error. This is simply the average of the square of the errors:

$$MSE = \frac{1}{n}\sum_i^n (y_i - \hat{y})^2$$

In [31]:
```
#Code task 8#
#Calculate the MSE as defined above
def mse(y, ypred):
    """Mean square error.

    Calculate the mean square error of the arguments

    Arguments:
    y -- the observed values
    ypred -- the predicted values
    """
    sq_error = (y - ypred)**2
    mse = np.mean(sq_error)
    return mse
```

In [26]:
```
mse(y_train, y_tr_pred)
```
Out[26]:
```
614.1334096969057
```

In [32]:
```
mse(y_test, y_te_pred)
```
Out[32]:
```
581.4365441953481
```

So here, you get a slightly better MSE on the test set than you did on the train set. And what does a squared error mean anyway? To convert this back to our measurement space, we often take the square root, to form the *root mean square error* thus:

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In [33]:
```
np.sqrt([mse(y_train, y_tr_pred), mse(y_test, y_te_pred)])
```

Out[33]:
```
array([24.78171523, 24.11299534])
```

4.7.2 sklearn metrics

Functions are good, but you don't want to have to define functions every time we want to assess performance. `sklearn.metrics` provides many commonly used metrics, included the ones above.

4.7.2.0.1 R-squared

In [34]:
```
r2_score(y_train, y_tr_pred), r2_score(y_test, y_te_pred)
```

Out[34]:
```
(0.0, -0.0031235200417913944)
```

4.7.2.0.2 Mean absolute error

In [35]:
```
mean_absolute_error(y_train, y_tr_pred), mean_absolute_error(y_test, y_te_p
```

Out[35]:
```
(17.92346371714677, 19.136142081278486)
```

4.7.2.0.3 Mean squared error

In [36]:
```
mean_squared_error(y_train, y_tr_pred), mean_squared_error(y_test, y_te_pre
```

Out[36]:
```
(614.1334096969046, 581.4365441953483)
```

4.7.3 Note On Calculating Metrics

When calling functions to calculate metrics, it is important to take care in the order of the arguments. Two of the metrics above actually don't care if the arguments are reversed; one does. Which one cares?

In a Jupyter code cell, running `r2_score?` will bring up the docstring for the function, and `r2_score??` will bring up the actual code of the function! Try them and compare the source for `sklearn` 's function with yours. Feel free to explore what happens when you reverse the order of the arguments and compare behaviour of `sklearn` 's function and yours.

In [37]:
```
# train set - sklearn
# correct order, incorrect order
r2_score(y_train, y_tr_pred), r2_score(y_tr_pred, y_train)
```

Out[37]:
```
(0.0, -3.041041349306602e+30)
```

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In [38]:
```
# test set - sklearn
# correct order, incorrect order
r2_score(y_test, y_te_pred), r2_score(y_te_pred, y_test)
```

Out[38]:
```
(-0.0031235200417913944, 0.0)
```

In [39]:
```
# train set - using our homebrew function
# correct order, incorrect order
r_squared(y_train, y_tr_pred), r_squared(y_tr_pred, y_train)
```

Out[39]:
```
(0.0, -3.041041349306602e+30)
```

In [40]:
```
# test set - using our homebrew function
# correct order, incorrect order
r_squared(y_test, y_te_pred), r_squared(y_te_pred, y_test)
```

```
/opt/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:15: Runt
imeWarning: divide by zero encountered in double_scalars
  from ipykernel import kernelapp as app
```

Out[40]:
```
(-0.0031235200417913944, -inf)
```

You can get very different results swapping the argument order. It's worth highlighting this because data scientists do this too much in the real world! Don't be one of them! Frequently the argument order doesn't matter, but it will bite you when you do it with a function that does care. It's sloppy, bad practice and if you don't make a habit of putting arguments in the right order, you will forget!

Remember:

- argument order matters,
- check function syntax with `func?` in a code cell

4.8 Initial Models

4.8.1 Imputing missing feature (predictor) values

Recall when performing EDA, you imputed (filled in) some missing values in pandas. You did this judiciously for exploratory/visualization purposes. You left many missing values in the data. You can impute missing values using scikit-learn, but note that you should learn values to impute from a train split and apply that to the test split to then assess how well your imputation worked.

4.8.1.1 Impute missing values with median

There's missing values. Recall from your data exploration that many distributions were skewed. Your first thought might be to impute missing values using the median.

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4.8.1.1.1 Learn the values to impute from the train set

In [41]:
```
# These are the values we'll use to fill in any missing values
X_defaults_median = X_train.median()
X_defaults_median
```

Out[41]:
```
summit_elev                            2215.000000
vertical_drop                           750.000000
base_elev                              1300.000000
trams                                     0.000000
fastSixes                                 0.000000
fastQuads                                 0.000000
quad                                      1.000000
triple                                    1.000000
double                                    1.000000
surface                                   2.000000
total_chairs                              7.000000
Runs                                     28.000000
TerrainParks                              2.000000
LongestRun_mi                             1.000000
SkiableTerrain_ac                       170.000000
Snow Making_ac                           96.500000
daysOpenLastYear                        109.000000
yearsOpen                                57.000000
averageSnowfall                         120.000000
projectedDaysOpen                       115.000000
NightSkiing_ac                           70.000000
resorts_per_state                        15.000000
resorts_per_100kcapita                    0.248243
resorts_per_100ksq_mile                  22.902162
resort_skiable_area_ac_state_ratio        0.051458
resort_days_open_state_ratio              0.071225
resort_terrain_park_state_ratio           0.069444
resort_night_skiing_state_ratio           0.077081
total_chairs_runs_ratio                   0.200000
total_chairs_skiable_ratio                0.040323
fastQuads_runs_ratio                      0.000000
fastQuads_skiable_ratio                   0.000000
dtype: float64
```

4.8.1.1.2 Apply the imputation to both train and test splits

In [42]:
```
#Code task 9#
#Call `X_train` and `X_test`'s `fillna()` method, passing `X_defaults_media
#Assign the results to `X_tr` and `X_te`, respectively
X_tr = X_train.fillna(X_defaults_median)
X_te = X_test.fillna(X_defaults_median)
```

4.8.1.1.3 Scale the data

As you have features measured in many different units, with numbers that vary by orders of magnitude, start off by scaling them to put them all on a consistent scale. The [StandardScaler (https://scikit-learn.org/stable/modules/generated/sklearn.preprocessing.StandardScaler.html)](https://scikit-learn.org/stable/modules/generated/sklearn.preprocessing.StandardScaler.html) scales each feature to zero mean and unit variance.

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In [43]:
```
#Code task 10#
#Call the StandardScaler`s fit method on `X_tr` to fit the scaler
#then use it's `transform()` method to apply the scaling to both the train
#data (`X_tr` and `X_te`), naming the results `X_tr_scaled` and `X_te_scale
scaler = StandardScaler()
scaler.fit(X_tr)
X_tr_scaled = scaler.transform(X_tr)
X_te_scaled = scaler.transform(X_te)
```

4.8.1.1.4 Train the model on the train split

In [117]:
```
lm = LinearRegression().fit(X_tr_scaled, y_train)
```

4.8.1.1.5 Make predictions using the model on both train and test splits

In [45]:
```
#Code task 11#
#Call the `predict()` method of the model (`lm`) on both the (scaled) train
#Assign the predictions to `y_tr_pred` and `y_te_pred`, respectively
y_tr_pred = lm.predict(X_tr_scaled)
y_te_pred = lm.predict(X_te_scaled)
```

4.8.1.1.6 Assess model performance

In [46]:
```
# r^2 - train, test
median_r2 = r2_score(y_train, y_tr_pred), r2_score(y_test, y_te_pred)
median_r2
```

Out[46]:
```
(0.8177988515690604, 0.7209725843435144)
```

Recall that you estimated ticket price by simply using a known average. As expected, this produced an R^2 of zero for both the training and test set, because R^2 tells us how much of the variance you're explaining beyond that of using just the mean, and you were using just the mean. Here we see that our simple linear regression model explains over 80% of the variance on the train set and over 70% on the test set. Clearly you are onto something, although the much lower value for the test set suggests you're overfitting somewhat. This isn't a surprise as you've made no effort to select a parsimonious set of features or deal with multicollinearity in our data.

In [47]:
```
#Code task 12#
#Now calculate the mean absolute error scores using `sklearn`'s `mean_absol
# as we did above for R^2
# MAE - train, test
median_mae = mean_absolute_error(y_train, y_tr_pred), mean_absolute_error(y
median_mae
```

Out[47]:
```
(8.547850301825424, 9.407020118581318)
```

Using this model, then, on average you'd expect to estimate a ticket price within $9 or so of the real price. This is much, much better than the $19 from just guessing using the average. There may be something to this machine learning lark after all!

Processing math: 100%

In [48]:
```
#Code task 13#
#And also do the same using `sklearn`'s `mean_squared_error`
# MSE - train, test
median_mse = mean_squared_error(y_train, y_tr_pred), mean_squared_error(y_t
median_mse
```

Out[48]:
```
(111.89581253658478, 161.73156451192273)
```

4.8.1.2 Impute missing values with the mean

You chose to use the median for filling missing values because of the skew of many of our predictor feature distributions. What if you wanted to try something else, such as the mean?

4.8.1.2.1 Learn the values to impute from the train set

Processing math: 100%

In [49]:
```
#Code task 14#
#As we did for the median above, calculate mean values for imputing missing
# These are the values we'll use to fill in any missing values
X_defaults_mean = X_train.mean()
X_defaults_mean
```

Out[49]:
```
summit_elev                          4074.554404
vertical_drop                        1043.196891
base_elev                            3020.512953
trams                                   0.103627
fastSixes                               0.072539
fastQuads                               0.673575
quad                                    1.010363
triple                                  1.440415
double                                  1.813472
surface                                 2.497409
total_chairs                            7.611399
Runs                                   41.188482
TerrainParks                            2.434783
LongestRun_mi                           1.293122
SkiableTerrain_ac                     448.785340
Snow Making_ac                        129.601190
daysOpenLastYear                      110.100629
yearsOpen                              56.559585
averageSnowfall                       162.310160
projectedDaysOpen                     115.920245
NightSkiing_ac                         86.384615
resorts_per_state                      16.264249
resorts_per_100kcapita                  0.424802
resorts_per_100ksq_mile                40.957785
resort_skiable_area_ac_state_ratio      0.097205
resort_days_open_state_ratio            0.126014
resort_terrain_park_state_ratio         0.116022
resort_night_skiing_state_ratio         0.155024
total_chairs_runs_ratio                 0.271441
total_chairs_skiable_ratio              0.070483
fastQuads_runs_ratio                    0.010401
fastQuads_skiable_ratio                 0.001633
dtype: float64
```

By eye, you can immediately tell that your replacement values are much higher than those from using the median.

4.8.1.2.2 Apply the imputation to both train and test splits

In [50]:
```
X_tr = X_train.fillna(X_defaults_mean)
X_te = X_test.fillna(X_defaults_mean)
```

4.8.1.2.3 Scale the data

Processing math: 100%

In [51]:
```
scaler = StandardScaler()
scaler.fit(X_tr)
X_tr_scaled = scaler.transform(X_tr)
X_te_scaled = scaler.transform(X_te)
```

4.8.1.2.4 Train the model on the train split

In [52]:
```
lm = LinearRegression().fit(X_tr_scaled, y_train)
```

4.8.1.2.5 Make predictions using the model on both train and test splits

In [53]:
```
y_tr_pred = lm.predict(X_tr_scaled)
y_te_pred = lm.predict(X_te_scaled)
```

4.8.1.2.6 Assess model performance

In [54]:
```
r2_score(y_train, y_tr_pred), r2_score(y_test, y_te_pred)
```

Out[54]:
```
(0.8170154093990025, 0.7163814716959965)
```

In [55]:
```
mean_absolute_error(y_train, y_tr_pred), mean_absolute_error(y_test, y_te_p
```

Out[55]:
```
(8.536884040670973, 9.416375625789271)
```

In [56]:
```
mean_squared_error(y_train, y_tr_pred), mean_squared_error(y_test, y_te_pre
```

Out[56]:
```
(112.37695054778276, 164.39269309524335)
```

These results don't seem very different to when you used the median for imputing missing values. Perhaps it doesn't make much difference here. Maybe your overtraining dominates. Maybe other feature transformations, such as taking the log, would help. You could try with just a subset of features rather than using all of them as inputs.

To perform the median/mean comparison, you copied and pasted a lot of code just to change the function for imputing missing values. It would make more sense to write a function that performed the sequence of steps:

1. impute missing values
2. scale the features
3. train a model
4. calculate model performance

But these are common steps and `sklearn` provides something much better than writing custom functions.

4.8.2 Pipelines

Processing math: 100%

One of the most important and useful components of `sklearn` is the [pipeline (https://scikit-learn.org/stable/modules/generated/sklearn.pipeline.Pipeline.html)](https://scikit-learn.org/stable/modules/generated/sklearn.pipeline.Pipeline.html). In place of `panda` 's `fillna` DataFrame method, there is `sklearn` 's `SimpleImputer` . Remember the first linear model above performed the steps:

1. replace missing values with the median for each feature
2. scale the data to zero mean and unit variance
3. train a linear regression model

and all these steps were trained on the train split and then applied to the test split for assessment.

The pipeline below defines exactly those same steps. Crucially, the resultant `Pipeline` object has a `fit()` method and a `predict()` method, just like the `LinearRegression()` object itself. Just as you might create a linear regression model and train it with `.fit()` and predict with `.predict()` , you can wrap the entire process of imputing and feature scaling and regression in a single object you can train with `.fit()` and predict with `.predict()` . And that's basically a pipeline: a model on steroids.

4.8.2.1 Define the pipeline

In [57]:
```
pipe = make_pipeline(
    SimpleImputer(strategy='median'),
    StandardScaler(),
    LinearRegression()
)
```

In [58]:
```
type(pipe)
```

Out[58]:
```
sklearn.pipeline.Pipeline
```

In [59]:
```
hasattr(pipe, 'fit'), hasattr(pipe, 'predict')
```

Out[59]:
```
(True, True)
```

4.8.2.2 Fit the pipeline

Here, a single call to the pipeline's `fit()` method combines the steps of learning the imputation (determining what values to use to fill the missing ones), the scaling (determining the mean to subtract and the variance to divide by), and then training the model. It does this all in the one call with the training data as arguments.

Processing math: 100%

In [60]:
```
#Code task 15#
#Call the pipe's `fit()` method with `X_train` and `y_train` as arguments
pipe.fit(X_train, y_train)
```

Out[60]:
```
Pipeline(memory=None,
         steps=[('simpleimputer',
                 SimpleImputer(add_indicator=False, copy=True, fill_value
=None,
                               missing_values=nan, strategy='median',
                               verbose=0)),
                ('standardscaler',
                 StandardScaler(copy=True, with_mean=True, with_std=Tru
e)),
                ('linearregression',
                 LinearRegression(copy_X=True, fit_intercept=True, n_jobs
=None,
                                  normalize=False))],
         verbose=False)
```

4.8.2.3 Make predictions on the train and test sets

In [61]:
```
y_tr_pred = pipe.predict(X_train)
y_te_pred = pipe.predict(X_test)
```

4.8.2.4 Assess performance

In [62]:
```
r2_score(y_train, y_tr_pred), r2_score(y_test, y_te_pred)
```

Out[62]:
```
(0.8177988515690604, 0.7209725843435144)
```

And compare with your earlier (non-pipeline) result:

In [63]:
```
median_r2
```

Out[63]:
```
(0.8177988515690604, 0.7209725843435144)
```

In [64]:
```
mean_absolute_error(y_train, y_tr_pred), mean_absolute_error(y_test, y_te_p
```

Out[64]:
```
(8.547850301825424, 9.407020118581318)
```

In [ ]:
```
Compare with your earlier result:
```

In [65]:
```
median_mae
```

Out[65]:
```
(8.547850301825424, 9.407020118581318)
```

In [66]:
```
mean_squared_error(y_train, y_tr_pred), mean_squared_error(y_test, y_te_pre
```

Out[66]:
```
(111.89581253658478, 161.73156451192273)
```

Processing math: 100%

Compare with your earlier result:

In [67]:
```
median_mse
```

Out[67]:
```
(111.89581253658478, 161.73156451192273)
```

These results confirm the pipeline is doing exactly what's expected, and results are identical to your earlier steps. This allows you to move faster but with confidence.

4.9 Refining The Linear Model

You suspected the model was overfitting. This is no real surprise given the number of features you blindly used. It's likely a judicious subset of features would generalize better. `sklearn` has a number of feature selection functions available. The one you'll use here is `SelectKBest` which, as you might guess, selects the k best features. You can read about SelectKBest [here (https://scikit-learn.org/stable/modules/generated/sklearn.feature_selection.SelectKBest.html#sklearn.feature_sele](https://scikit-learn.org/stable/modules/generated/sklearn.feature_selection.SelectKBest.html#sklearn.feature_sele) `f_regression` is just the [score function (https://scikit-learn.org/stable/modules/generated/sklearn.feature_selection.f_regression.html#sklearn.feature_sele](https://scikit-learn.org/stable/modules/generated/sklearn.feature_selection.f_regression.html#sklearn.feature_sele) you're using because you're performing regression. It's important to choose an appropriate one for your machine learning task.

4.9.1 Define the pipeline

Redefine your pipeline to include this feature selection step:

In [68]:
```
#Code task 16#
#Add `SelectKBest` as a step in the pipeline between `StandardScaler()` and
#Don't forget to tell it to use `f_regression` as its score function
pipe = make_pipeline(
    SimpleImputer(strategy='median'),
    StandardScaler(),
    SelectKBest(f_regression),
    LinearRegression()
)
```

4.9.2 Fit the pipeline

Processing math: 100%

In [69]:
```
pipe.fit(X_train, y_train)
```

Out[69]:
```
Pipeline(memory=None,
         steps=[('simpleimputer',
                 SimpleImputer(add_indicator=False, copy=True, fill_value
=None,
                               missing_values=nan, strategy='median',
                               verbose=0)),
                ('standardscaler',
                 StandardScaler(copy=True, with_mean=True, with_std=Tru
e)),
                ('selectkbest',
                 SelectKBest(k=10,
                             score_func=<function f_regression at 0x1a22b
61e60>)),
                ('linearregression',
                 LinearRegression(copy_X=True, fit_intercept=True, n_jobs
=None,
                                  normalize=False))],
         verbose=False)
```

4.9.3 Assess performance on the train and test set

In [70]:
```
y_tr_pred = pipe.predict(X_train)
y_te_pred = pipe.predict(X_test)
```

In [71]:
```
r2_score(y_train, y_tr_pred), r2_score(y_test, y_te_pred)
```

Out[71]:
```
(0.7674914326052744, 0.6259877354190837)
```

In [72]:
```
mean_absolute_error(y_train, y_tr_pred), mean_absolute_error(y_test, y_te_p
```

Out[72]:
```
(9.501495079727484, 11.201830190332052)
```

This has made things worse! Clearly selecting a subset of features has an impact on performance. `SelectKBest` defaults to k=10. You've just seen that 10 is worse than using all features. What is the best k? You could create a new pipeline with a different value of k:

4.9.4 Define a new pipeline to select a different number of features

In [73]:
```
#Code task 17#
#Modify the `SelectKBest` step to use a value of 15 for k
pipe15 = make_pipeline(
    SimpleImputer(strategy='median'),
    StandardScaler(),
    SelectKBest(f_regression, k=15),
    LinearRegression()
)
```

Processing math: 100%

4.9.5 Fit the pipeline

In [74]:
```
pipe15.fit(X_train, y_train)
```

Out[74]:
```
Pipeline(memory=None,
         steps=[('simpleimputer',
                 SimpleImputer(add_indicator=False, copy=True, fill_value
=None,
                               missing_values=nan, strategy='median',
                               verbose=0)),
                ('standardscaler',
                 StandardScaler(copy=True, with_mean=True, with_std=Tru
e)),
                ('selectkbest',
                 SelectKBest(k=15,
                             score_func=<function f_regression at 0x1a22b
61e60>)),
                ('linearregression',
                 LinearRegression(copy_X=True, fit_intercept=True, n_jobs
=None,
                                  normalize=False))],
         verbose=False)
```

4.9.6 Assess performance on train and test data

In [75]:
```
y_tr_pred = pipe15.predict(X_train)
y_te_pred = pipe15.predict(X_test)
```

In [76]:
```
r2_score(y_train, y_tr_pred), r2_score(y_test, y_te_pred)
```

Out[76]:
```
(0.7924096060483825, 0.6376199973170795)
```

In [77]:
```
mean_absolute_error(y_train, y_tr_pred), mean_absolute_error(y_test, y_te_p
```

Out[77]:
```
(9.211767769307114, 10.488246867294357)
```

You could keep going, trying different values of k, training a model, measuring performance on the test set, and then picking the model with the best test set performance. There's a fundamental problem with this approach: *you're tuning the model to the arbitrary test set_! If you continue this way you'll end up with a model works well on the particular quirks of our test set _but fails to generalize to new data*. The whole point of keeping a test set is for it to be a set of that new data, to check how well our model might perform on data it hasn't seen.

The way around this is a technique called *cross-validation*. You partition the training set into k folds, train our model on k-1 of those folds, and calculate performance on the fold not used in training. This procedure then cycles through k times with a different fold held back each time. Thus you end up building k models on k sets of data with k estimates of how the model performs on unseen data but without having to touch the test set.

4.9.7 Assessing performance using cross-validation

In [78]:
```
cv_results = cross_validate(pipe15, X_train, y_train, cv=5)
```

In [79]:
```
cv_scores = cv_results['test_score']
cv_scores
```

Out[79]:
```
array([0.63760862, 0.72831381, 0.74443537, 0.5487915 , 0.50441472])
```

Without using the same random state for initializing the CV folds, your actual numbers will be different.

In [80]:
```
np.mean(cv_scores), np.std(cv_scores)
```

Out[80]:
```
(0.6327128053007863, 0.09502487849877697)
```

These results highlight that assessing model performance in inherently open to variability. You'll get different results depending on the quirks of which points are in which fold. An advantage of this is that you can also obtain an estimate of the variability, or uncertainty, in your performance estimate.

In [81]:
```
np.round((np.mean(cv_scores) - 2 * np.std(cv_scores), np.mean(cv_scores) +
```

Out[81]:
```
array([0.44, 0.82])
```

4.9.8 Hyperparameter search using GridSearchCV

Pulling the above together, we have:

- a pipeline that
  - imputes missing values
  - scales the data
  - selects the k best features
  - trains a linear regression model
- a technique (cross-validation) for estimating model performance

Now you want to use cross-validation for multiple values of k and use cross-validation to pick the value of k that gives the best performance. `make_pipeline` automatically names each step as the lowercase name of the step and the parameters of the step are then accessed by appending a double underscore followed by the parameter name. You know the name of the step will be 'selectkbest' and you know the parameter is 'k'.

You can also list the names of all the parameters in a pipeline like this:

Processing math: 100%

In [82]:
```
#Code task 18#
#Call `pipe`'s `get_params()` method to get a dict of available parameters
#using dict's `keys()` method
pipe.get_params().keys()
```

Out[82]:
```
dict_keys(['memory', 'steps', 'verbose', 'simpleimputer', 'standardscale
r', 'selectkbest', 'linearregression', 'simpleimputer__add_indicator', 's
impleimputer__copy', 'simpleimputer__fill_value', 'simpleimputer__missing
_values', 'simpleimputer__strategy', 'simpleimputer__verbose', 'standards
caler__copy', 'standardscaler__with_mean', 'standardscaler__with_std', 's
electkbest__k', 'selectkbest__score_func', 'linearregression__copy_X', 'l
inearregression__fit_intercept', 'linearregression__n_jobs', 'linearregre
ssion__normalize'])
```

The above can be particularly useful as your pipelines becomes more complex (you can even nest pipelines within pipelines).

In [83]:
```
k = [k+1 for k in range(len(X_train.columns))]
grid_params = {'selectkbest__k': k}
```

Now you have a range of `k` to investigate. Is 1 feature best? 2? 3? 4? All of them? You could write a for loop and iterate over each possible value, doing all the housekeeping oyurselves to track the best value of k. But this is a common task so there's a built in function in `sklearn`. This is `GridSearchCV` [(https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.GridSearchCV.html)](https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.GridSearchCV.html). This takes the pipeline object, in fact it takes anything with a `.fit()` and `.predict()` method. In simple cases with no feature selection or imputation or feature scaling etc. you may see the classifier or regressor object itself directly passed into `GridSearchCV`. The other key input is the parameters and values to search over. Optional parameters include the cross-validation strategy and number of CPUs to use.

In [84]:
```
lr_grid_cv = GridSearchCV(pipe, param_grid=grid_params, cv=5, n_jobs=-1)
```

Processing math: 100%

In [85]:
```
lr_grid_cv.fit(X_train, y_train)
```

Out[85]:
```
GridSearchCV(cv=5, error_score=nan,
             estimator=Pipeline(memory=None,
                                steps=[('simpleimputer',
                                        SimpleImputer(add_indicator=Fals
e,
                                                      copy=True,
                                                      fill_value=None,
                                                      missing_values=nan,
                                                      strategy='median',
                                                      verbose=0)),
                                       ('standardscaler',
                                        StandardScaler(copy=True,
                                                       with_mean=True,
                                                       with_std=True)),
                                       ('selectkbest',
                                        SelectKBest(k=10,
                                                    score_func=<function
f_regression at 0x1a22b61e60>)),
                                       ('linearregression',
                                        LinearRegression(copy_X=True,
                                                         fit_intercept=Tr
ue,

                                                         n_jobs=None,
                                                         normalize=Fals
e))],
                                verbose=False),
             iid='deprecated', n_jobs=-1,
             param_grid={'selectkbest__k': [1, 2, 3, 4, 5, 6, 7, 8, 9, 1
0, 11,
                                            12, 13, 14, 15, 16, 17, 18, 1
9, 20,
                                            21, 22, 23, 24, 25, 26, 27, 2
8, 29,
                                            30, ...]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=Fals
e,
             scoring=None, verbose=0)
```

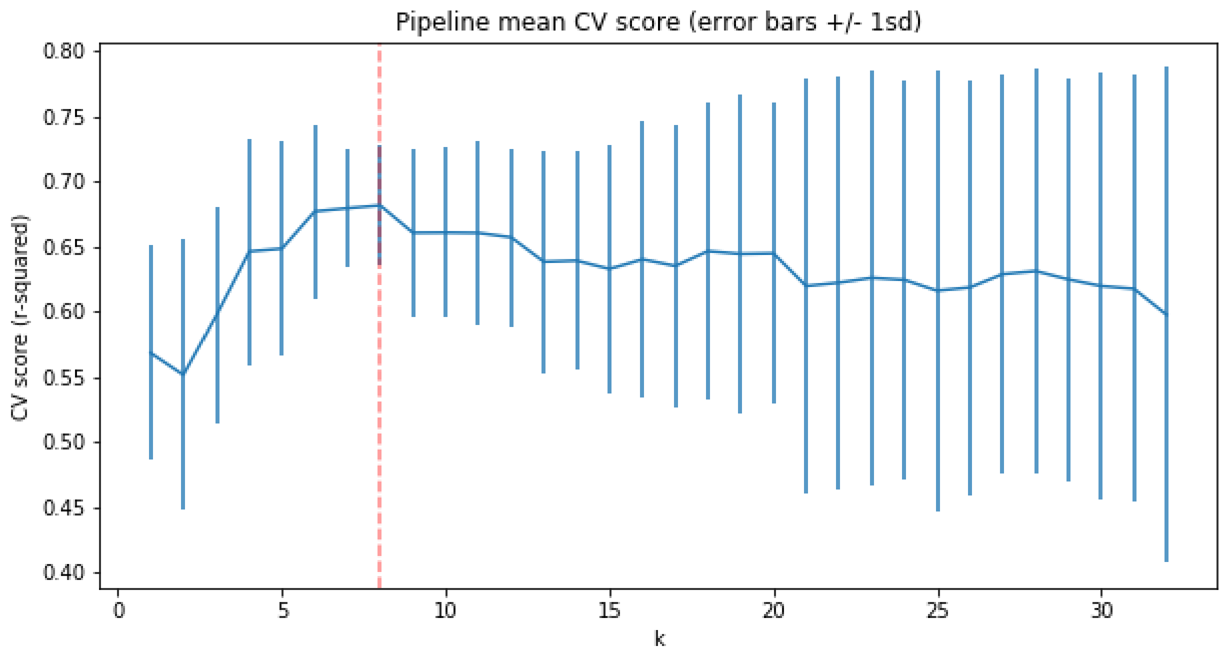
In [86]:
```
score_mean = lr_grid_cv.cv_results_['mean_test_score']
score_std = lr_grid_cv.cv_results_['std_test_score']
cv_k = [k for k in lr_grid_cv.cv_results_['param_selectkbest__k']]
```

In [87]:
```
#Code task 19#
#Print the `best_params_` attribute of `lr_grid_cv`
lr_grid_cv.best_params_
```

Out[87]:
```
{'selectkbest__k': 8}
```

Processing math: 100%

In [88]:
```
#Code task 20#
#Assign the value of k from the above dict of `best_params_` and assign it
best_k = lr_grid_cv.best_params_['selectkbest__k']
plt.subplots(figsize=(10, 5))
plt.errorbar(cv_k, score_mean, yerr=score_std)
plt.axvline(x=best_k, c='r', ls='--', alpha=.5)
plt.xlabel('k')
plt.ylabel('CV score (r-squared)')
plt.title('Pipeline mean CV score (error bars +/- 1sd)');
```



The above suggests a good value for k is 8. There was an initial rapid increase with k, followed by a slow decline. Also noticeable is the variance of the results greatly increase above k=8. As you increasingly overfit, expect greater swings in performance as different points move in and out of the train/test folds.

Which features were most useful? Step into your best model, shown below. Starting with the fitted grid search object, you get the best estimator, then the named step 'selectkbest', for which you can its `get_support()` method for a logical mask of the features selected.

In [89]:
```
selected = lr_grid_cv.best_estimator_.named_steps.selectkbest.get_support()
```

Similarly, instead of using the 'selectkbest' named step, you can access the named step for the linear regression model and, from that, grab the model coefficients via its `coef_` attribute:

Processing math: 100%

In [90]:
```
#Code task 21#
#Get the linear model coefficients from the `coef_` attribute and store in
#get the matching feature names from the column names of the dataframe,
#and display the results as a pandas Series with `coefs` as the values and
#sorting the values in descending order
coefs = lr_grid_cv.best_estimator_.named_steps.linearregression.coef_
features = X_train.columns[selected]
pd.Series(coefs, index=features).sort_values(ascending=False)
```

Out[90]:
```
vertical_drop        10.767857
Snow Making_ac        6.290074
total_chairs          5.794156
fastQuads             5.745626
Runs                  5.370555
LongestRun_mi         0.181814
trams                -4.142024
SkiableTerrain_ac    -5.249780
dtype: float64
```

These results suggest that vertical drop is your biggest positive feature. This makes intuitive sense and is consistent with what you saw during the EDA work. Also, you see the area covered by snow making equipment is a strong positive as well. People like guaranteed skiing! The skiable terrain area is negatively associated with ticket price! This seems odd. People will pay less for larger resorts? There could be all manner of reasons for this. It could be an effect whereby larger resorts can host more visitors at any one time and so can charge less per ticket. As has been mentioned previously, the data are missing information about visitor numbers. Bear in mind, the coefficient for skiable terrain is negative *for this model*. For example, if you kept the total number of chairs and fastQuads constant, but increased the skiable terrain extent, you might imagine the resort is worse off because the chairlift capacity is stretched thinner.

4.10 Random Forest Model

A model that can work very well in a lot of cases is the random forest. For regression, this is provided by `sklearn`'s `RandomForestRegressor` class.

Time to stop the bad practice of repeatedly checking performance on the test split. Instead, go straight from defining the pipeline to assessing performance using cross-validation. `cross_validate` will perform the fitting as part of the process. This uses the default settings for the random forest so you'll then proceed to investigate some different hyperparameters.

4.10.1 Define the pipeline

Processing math: 100%

In [92]:
```
#Code task 22#
#Define a pipeline comprising the steps:
#SimpleImputer() with a strategy of 'median'
#StandardScaler(),
#and then RandomForestRegressor() with a random state of 47
RF_pipe = make_pipeline(
    SimpleImputer(strategy='median'),
    StandardScaler(),
    RandomForestRegressor(random_state=47)
)
```

4.10.2 Fit and assess performance using cross-validation

In [93]:
```
#Code task 23#
#Call `cross_validate` to estimate the pipeline's performance.
#Pass it the random forest pipe object, `X_train` and `y_train`,
#and get it to use 5-fold cross-validation
rf_default_cv_results = cross_validate(RF_pipe, X_train, y_train, cv=5)
```

In [94]:
```
rf_cv_scores = rf_default_cv_results['test_score']
rf_cv_scores
```

Out[94]:
```
array([0.6877383 , 0.77987845, 0.77753583, 0.62190924, 0.61794573])
```

In [95]:
```
np.mean(rf_cv_scores), np.std(rf_cv_scores)
```

Out[95]:
```
(0.6970015087370294, 0.07117420491358241)
```

4.10.3 Hyperparameter search using GridSearchCV

Random forest has a number of hyperparameters that can be explored, however here you'll limit yourselves to exploring some different values for the number of trees. You'll try it with and without feature scaling, and try both the mean and median as strategies for imputing missing values.

Processing math: 100%

In [96]:
```
n_est = [int(n) for n in np.logspace(start=1, stop=3, num=20)]
grid_params = {
        'randomforestregressor__n_estimators': n_est,
        'standardscaler': [StandardScaler(), None],
        'simpleimputer__strategy': ['mean', 'median']
}
grid_params
```

Out[96]:
```
{'randomforestregressor__n_estimators': [10,
  12,
  16,
  20,
  26,
  33,
  42,
  54,
  69,
  88,
  112,
  143,
  183,
  233,
  297,
  379,
  483,
  615,
  784,
  1000],
 'standardscaler': [StandardScaler(copy=True, with_mean=True, with_std=Tr
ue),
  None],
 'simpleimputer__strategy': ['mean', 'median']}
```

In [97]:
```
#Code task 24#
#Call `GridSearchCV` with the random forest pipeline, passing in the above
#dict for parameters to evaluate, 5-fold cross-validation, and all availabl
rf_grid_cv = GridSearchCV(RF_pipe, param_grid=grid_params, cv=5, n_jobs=-1)
```

Processing math: 100%

In [98]:
```
#Code task 25#
#Now call the `GridSearchCV`'s `fit()` method with `X_train` and `y_train`
#to actually start the grid search. This may take a minute or two.
rf_grid_cv.fit(X_train, y_train)
```

Out[98]:
```
GridSearchCV(cv=5, error_score=nan,
             estimator=Pipeline(memory=None,
                                steps=[('simpleimputer',
                                        SimpleImputer(add_indicator=Fals
e,
                                                      copy=True,
                                                      fill_value=None,
                                                      missing_values=nan,
                                                      strategy='median',
                                                      verbose=0)),
                                       ('standardscaler',
                                        StandardScaler(copy=True,
                                                       with_mean=True,
                                                       with_std=True)),
                                       ('randomforestregressor',
                                        RandomForestRegressor(bootstrap=T
rue,
                                                              ccp_alpha=
0.0,
                                                              cr...
             iid='deprecated', n_jobs=-1,
             param_grid={'randomforestregressor__n_estimators': [10, 12,
16, 20,
                                                                 26, 33,
42, 54,
                                                                 69, 88,
112,
                                                                 143, 18
3, 233,
                                                                 297, 37
9, 483,
                                                                 615, 78
4,
                                                                 1000],
                         'simpleimputer__strategy': ['mean', 'median'],
                         'standardscaler': [StandardScaler(copy=True,
                                                           with_mean=Tru
e,
                                                           with_std=Tru
e),
                                            None]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=Fals
e,
             scoring=None, verbose=0)
```

Processing math: 100%

In [99]:
```
#Code task 26#
#Print the best params (`best_params_` attribute) from the grid search
rf_grid_cv.best_params_
```

Out[99]:
```
{'randomforestregressor__n_estimators': 69,
 'simpleimputer__strategy': 'median',
 'standardscaler': None}
```

It looks like imputing with the median helps, but scaling the features doesn't.

In [100]:
```
rf_best_cv_results = cross_validate(rf_grid_cv.best_estimator_, X_train, y_
rf_best_scores = rf_best_cv_results['test_score']
rf_best_scores
```

Out[100]:
```
array([0.68961442, 0.79593861, 0.77128447, 0.62254707, 0.66142192])
```

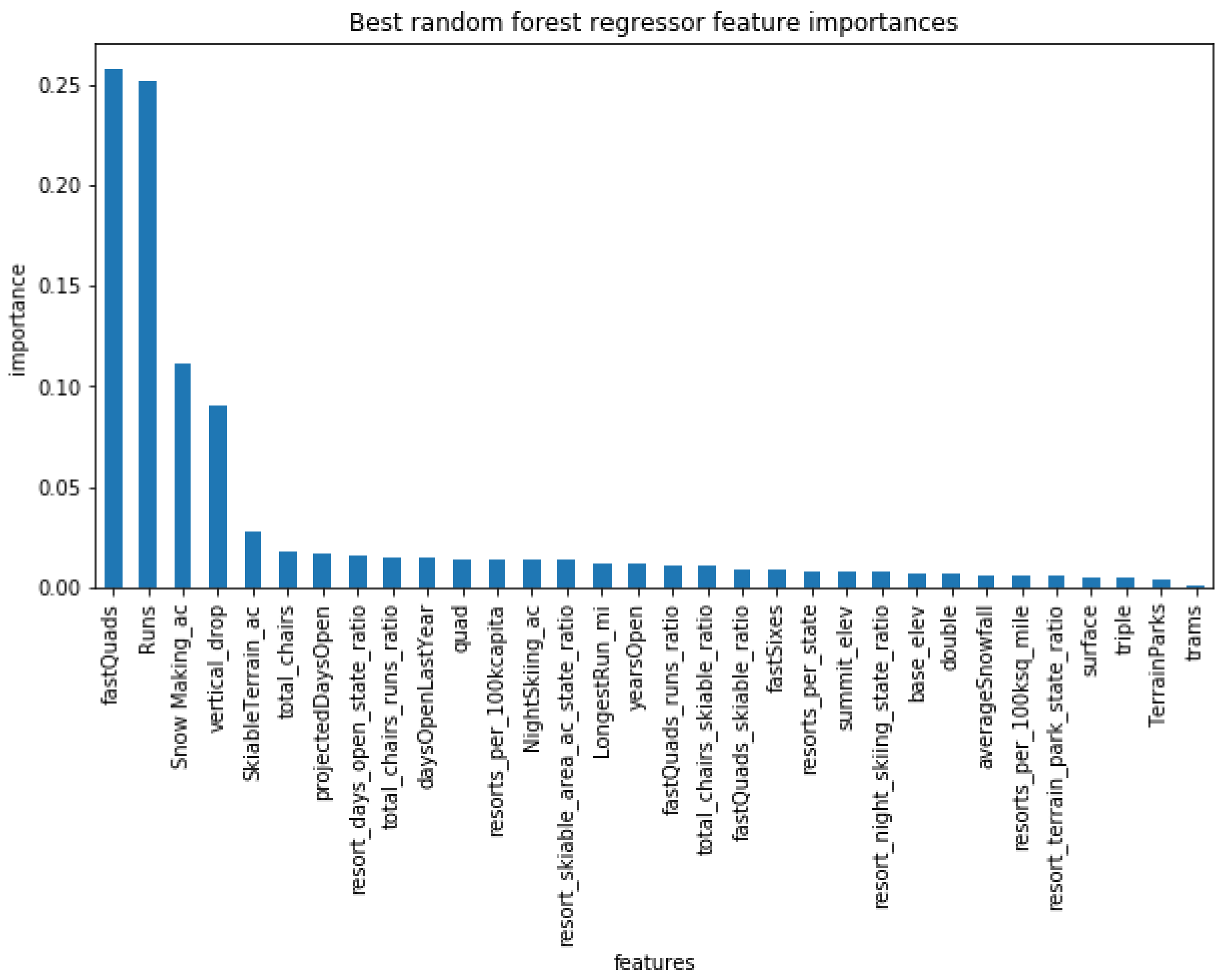
In [101]:
```
np.mean(rf_best_scores), np.std(rf_best_scores)
```

Out[101]:
```
(0.7081612973109424, 0.06564715369819316)
```

You've marginally improved upon the default CV results. Random forest has many more hyperparameters you could tune, but we won't dive into that here.

Processing math: 100%

In [102]:
```
#Code task 27#
#Plot a barplot of the random forest's feature importances,
#assigning the `feature_importances_` attribute of
#`rf_grid_cv.best_estimator_.named_steps.randomforestregressor` to the name
#create a pandas Series object of the feature importances, with the index g
#training data column names, sorting the values in descending order
plt.subplots(figsize=(10, 5))
imps = rf_grid_cv.best_estimator_.named_steps.randomforestregressor.feature
rf_feat_imps = pd.Series(imps, index=X_train.columns).sort_values(ascending
rf_feat_imps.plot(kind='bar')
plt.xlabel('features')
plt.ylabel('importance')
plt.title('Best random forest regressor feature importances');
```



Encouragingly, the dominant top four features are in common with your linear model:

- fastQuads
- Runs
- Snow Making_ac
- vertical_drop

4.11 Final Model Selection

Processing math: 100%

Time to select your final model to use for further business modeling! It would be good to revisit the above model selection; there is undoubtedly more that could be done to explore possible hyperparameters. It would also be worthwhile to investigate removing the least useful features. Gathering or calculating, and storing, features adds business cost and dependencies, so if features genuinely are not needed they should be removed. Building a simpler model with fewer features can also have the advantage of being easier to sell (and/or explain) to stakeholders. Certainly there seem to be four strong features here and so a model using only those would probably work well. However, you want to explore some different scenarios where other features vary so keep the fuller model for now. The business is waiting for this model and you have something that you have confidence in to be much better than guessing with the average price.

Or, rather, you have two "somethings". You built a best linear model and a best random forest model. You need to finally choose between them. You can calculate the mean absolute error using cross-validation. Although `cross-validate` defaults to the R^2 [metric for scoring (https://scikit-learn.org/stable/modules/model_evaluation.html#scoring)](https://scikit-learn.org/stable/modules/model_evaluation.html#scoring) regression, you can specify the mean absolute error as an alternative via the `scoring` parameter.

4.11.1 Linear regression model performance

In [103]:
```
# 'neg_mean_absolute_error' uses the (negative of) the mean absolute error
lr_neg_mae = cross_validate(lr_grid_cv.best_estimator_, X_train, y_train,
                            scoring='neg_mean_absolute_error', cv=5, n_jobs
```

In [104]:
```
lr_mae_mean = np.mean(-1 * lr_neg_mae['test_score'])
lr_mae_std = np.std(-1 * lr_neg_mae['test_score'])
lr_mae_mean, lr_mae_std
```

Out[104]:
```
(10.499032338015294, 1.6220608976799664)
```

In [105]:
```
mean_absolute_error(y_test, lr_grid_cv.best_estimator_.predict(X_test))
```

Out[105]:
```
11.793465668669327
```

4.11.2 Random forest regression model performance

In [106]:
```
rf_neg_mae = cross_validate(rf_grid_cv.best_estimator_, X_train, y_train,
                            scoring='neg_mean_absolute_error', cv=5, n_jobs
```

In [107]:
```
rf_mae_mean = np.mean(-1 * rf_neg_mae['test_score'])
rf_mae_std = np.std(-1 * rf_neg_mae['test_score'])
rf_mae_mean, rf_mae_std
```

Out[107]:
```
(9.659539811066127, 1.3496029127071227)
```

Processing math: 100%

In [120]:
```
y_predict_test = rf_grid_cv.best_estimator_.predict(X_test)
residuals_test = y_test - y_predict_test
print(residuals_test)
```

```
119     -8.086957
195    -11.512174
115    -13.507246
102     -4.729565
167      0.591304
          ...
223     41.127536
76      -5.130435
241      6.359420
254      0.753913
45     -11.304348
Name: AdultWeekend, Length: 83, dtype: float64
```

In [119]:
```
mean_absolute_error(y_test, y_predict_test)
```

Out[119]:
```
9.495505500261919
```

4.11.3 Conclusion

The random forest model has a lower cross-validation mean absolute error by almost $1. It also exhibits less variability. Verifying performance on the test set produces performance consistent with the cross-validation results.

4.12 Data quantity assessment

Finally, you need to advise the business whether it needs to undertake further data collection. Would more data be useful? We're often led to believe more data is always good, but gathering data invariably has a cost associated with it. Assess this trade off by seeing how performance varies with differing data set sizes. The `learning_curve` function does this conveniently.

In [109]:
```
fractions = [.2, .25, .3, .35, .4, .45, .5, .6, .75, .8, 1.0]
train_size, train_scores, test_scores = learning_curve(pipe, X_train, y_tra
train_scores_mean = np.mean(train_scores, axis=1)
train_scores_std = np.std(train_scores, axis=1)
test_scores_mean = np.mean(test_scores, axis=1)
test_scores_std = np.std(test_scores, axis=1)
```

Processing math: 100%

In [110]:
```
plt.subplots(figsize=(10, 5))
plt.errorbar(train_size, test_scores_mean, yerr=test_scores_std)
plt.xlabel('Training set size')
plt.ylabel('CV scores')
plt.title('Cross-validation score as training set size increases');
```

This shows that you seem to have plenty of data. There's an initial rapid improvement in model scores as one would expect, but it's essentially levelled off by around a sample size of 40-50.

4.13 Save best model object from pipeline

Processing math: 100%

In [116]:
```
#Code task 28#
#This may not be "production grade ML deployment" practice, but adding some
#information to your saved models can save your bacon in development.
#Just what version model have you just loaded to reuse? What version of `sk
#created it? When did you make it?
#Assign the pandas version number (`pd.__version__`) to the `pandas_version
#the numpy version (`np.__version__`) to the `numpy_version` attribute,
#the sklearn version (`sklearn_version`) to the `sklearn_version` attribute
#and the current datetime (`datetime.datetime.now()`) to the `build_datetim
#Let's call this model version '1.0'
best_model = rf_grid_cv.best_estimator_
best_model.version = '1.0'
best_model.pandas_version = 'pd._version_'
best_model.numpy_version = 'np._version_'
best_model.sklearn_version = 'sklearn_version'
best_model.X_columns = [col for col in X_train.columns]
best_model.build_datetime = 'datetime.datetime.now()'

modelpath = 'models'
if not os.path.exists(modelpath):
    os.mkdir(modelpath)
skimodel_path = os.path.join(modelpath, 'ski_resort_pricing_model.pkl')
if not os.path.exists(skimodel_path):
    with open(skimodel_path, 'wb') as f:
        pickle.dump(best_model, f)
```

4.14 Summary

Q: 1 Write a summary of the work in this notebook. Capture the fact that you gained a baseline idea of performance by simply taking the average price and how well that did. Then highlight that you built a linear model and the features that found. Comment on the estimate of its performance from cross-validation and whether its performance on the test split was consistent with this estimate. Also highlight that a random forest regressor was tried, what preprocessing steps were found to be best, and again what its estimated performance via cross-validation was and whether its performance on the test set was consistent with that. State which model you have decided to use going forwards and why. This summary should provide a quick overview for someone wanting to know quickly why the given model was chosen for the next part of the business problem to help guide important business decisions.

A: 1 Your answer here

Processing math: 100%