Zuehlke DAMLAS Target DS Homework - 18aug2016

August 19, 2016

In [1]:
```
%%javascript
/*************************************************************************
Known Mathjax Issue with Chrome - a rounding issue adds a border to the rig
https://github.com/mathjax/MathJax/issues/1300
A quick hack to fix this based on stackoverflow discussions:
http://stackoverflow.com/questions/34277967/chrome-rendering-mathjax-equati
**************************************************************************

$('.math>span').css("border-left-color","transparent")
```

```
<IPython.core.display.Javascript object>
```

In [2]:
```
%reload_ext autoreload
%autoreload 2
```

1 DAMLAS - Machine Learning At Scale

1.1 Assignment - HW4

Data Analytics and Machine Learning at Scale Target, Minneapolis

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Week: 04

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1 Instructions Back to Table of Contents * Homework submissions are due by Thursday, 08/18/2016 at 11AM (CT).

- Prepare a single Jupyter notebook (not a requirment), please include questions, and question numbers in the questions and in the responses. Submit your homework notebook via the following form:

- Submission Link - Google Form

2.0.1 Documents:

- IPython Notebook, published and viewable online.
- PDF export of IPython Notebook.

2 Useful References Back to Table of Contents

- Lecture Slides on Decision Trees and Ensembles

- Chapter 17 on decision Trees, https://www.dropbox.com/s/5ca98ah5chqlcmn/Data_Science_from_Scratcl [Please do not share this PDF]

- Karau, Holden, Konwinski, Andy, Wendell, Patrick, & Zaharia, Matei. (2015). Learning Spark: Lightning-fast big data analysis. Sebastopol, CA: O'Reilly Publishers.

- Hastie, Trevor, Tibshirani, Robert, & Friedman, Jerome. (2009). The elements of statistical learning: Data mining, inference, and prediction (2nd ed.). Stanford, CA: Springer Science+Business Media. **(Download for free here)**

- **2.1 Ryza, Sandy, Laserson, Uri, Owen, Sean, & Wills, Josh. (2015). Advanced analytics with Spark: Patterns for learning from data at scale. Sebastopol, CA: O'Reilly Publishers.**

2.2 3. HW4

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HW4.0 Final Project description

Please prepare your project description using the following format * 200 words abstract * data source and description * pipeline of steps (in a block diagram) * Metrics for success

PLEASE NOTE: We will probably have project team sizes of 3 people plus/minus 1

https://github.com/zuehlkescott5/MachineLearning/blob/master/TargetDataScienceTraining/Week%202

HW4.1 Build a decision to predict whether you can play tennis or not

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Decision Trees

Write a program in Python (or in Spark; this part is optional) to implement the ID3 decision tree algorithm. You should build a tree to predict PlayTennis, based on the other attributes (but, do not use the Day attribute in your tree.). You should read in a space delimited dataset in a file called dataset.txt and output to the screen your decision tree and the training set accuracy in some readable format. For example, here is the tennis dataset. The first line will contain the names of the fields:

The last column is the classification attribute, and will always contain contain the values yes or no.

For output, you can choose how to draw the tree so long as it is clear what the tree is. You might find it easier if you turn the decision tree on its side, and use indentation to show levels of the tree as it grows from the left. For example:

You don't need to make your tree output look exactly like above: feel free to print out something similarly readable if you think it is easier to code.

You may find Python dictionaries especially useful here, as they will give you a quick an easy way to help manage counting the number of times you see a particular attribute.

Here are some FAQs that I've gotten in the past regarding this assignment, and some I might get if I don't answer them now.

Should my code work for other datasets besides the tennis dataset? Yes. We will give your program a different dataset to try it out with. You may assume that our dataset is correct and well-formatted, but you should not make assumptions regrading number of rows, number of columns, or values that will appear within. The last column will also be the classification, and will always contain yes or no values.

Is it possible that some value, like "normal," could appear in more than one column? Yes. In addition to the column "humidity", we might have had another column called "skycolor" which could have values "normal," "weird," and "bizarre."

Could "yes" and "no" appear as possible values in columns other than the classification column? Yes. In addition to the classification column "playtennis," we might have had another column called "seasonalweather" which would contain "yes" and "no."

2.2.1 Write data set to text file.

```
In [3]: %%writefile playtennis41.txt
        Day outlook temperature humidity wind playtennis
        d1 sunny hot high FALSE no
        d2 sunny hot high TRUE no
        d3 overcast hot high FALSE yes
        d4 rainy mild high FALSE yes
        d5 rainy cool normal FALSE yes
        d6 rainy cool normal TRUE no
        d6 overcast cool normal TRUE yes
        d7 sunny mild high FALSE no
        d8 sunny cool normal FALSE yes
        d9 rainy mild normal FALSE yes
        d10 sunny mild normal TRUE yes
        d11 overcast mild high TRUE yes
        d12 overcast hot normal FALSE yes
        d13 rainy mild high TRUE no
```

```
Overwriting playtennis41.txt
```

2.2.2 Define objects required for decision tree build, classification, and evaluation.

```
In [4]: from __future__ import division
        from collections import Counter, defaultdict
        from functools import partial
        import math, random
        import pandas
        import numpy as np

        def entropy(class_probabilities):
            """given a list of class probabilities, compute the entropy"""
            return sum(-p * math.log(p, 2) for p in class_probabilities if p)

        def class_probabilities(labels):
            total_count = len(labels)
            return [count/total_count for count in Counter(labels).values()]

        def data_entropy(labeled_data):
            labels = [label for _, label in labeled_data]
            probabilities = class_probabilities(labels)
            return entropy(probabilities)

        def partition_entropy(subsets):
            """find the entropy from this partition of data into subsets"""
            total_count = sum(len(subset) for subset in subsets)
            return sum(data_entropy(subset)*len(subset)/total_count for subset in s

        def inputformat(fileName, delim, classifycolumn, differentiator):
            input_df = pandas.read_table(fileName, sep=delim)
            del input_df[differentiator]
            inputs = input_df.iloc[:,:len(input_df.columns)-1].T.to_dict().values()
            labels = input_df[[len(input_df.columns)-1]].T.to_dict().values()
            formattedInput = list(zip(inputs, [d[classifycolumn] for d in labels]))
            return formattedInput

        def group_by(items, key_fn):
            """returns a defaultdict(list), where each input item
            is in the list whose key is key_fn(item)"""
            groups = defaultdict(list)
            for item in items:
                key = key_fn(item)
                groups[key].append(item)
            return groups

        def partition_by(inputs, attribute):
```

```python
    """returns a dict of inputs partitioned by the attribute
    each input is a pair (attribute_dict, label)"""
    return group_by(inputs, lambda x: x[0][attribute])

def partition_entropy_by(inputs, attribute):
    """computes the entropy corresponding to the given partition"""
    partitions = partition_by(inputs, attribute)
    return partition_entropy(partitions.values())

def build_tree_id3(inputs, split_candidates=None):

    # if this is our first pass,
    # all keys of the first input are split candidates
    if split_candidates is None:
        split_candidates = inputs[0][0].keys()

    # count Trues and Falses in the inputs
    num_inputs = len(inputs)
    num_trues = [label for item, label in inputs if label].count('yes')
    num_falses = num_inputs - num_trues

    if num_trues == 0:                   # if only Falses are left
        return False                     # return a "False" leaf

    if num_falses == 0:                  # if only Trues are left
        return True                      # return a "True" leaf

    if not split_candidates:             # if no split candidates left
        return num_trues >= num_falses   # return the majority leaf

    # otherwise, split on the best attribute
    best_attribute = min(split_candidates,
        key=partial(partition_entropy_by, inputs))

    partitions = partition_by(inputs, best_attribute)
    new_candidates = [a for a in split_candidates
                      if a != best_attribute]

    # recursively build the subtrees
    subtrees = { attribute : build_tree_id3(subset, new_candidates)
                 for attribute, subset in partitions.iteritems() }

    subtrees[None] = num_trues > num_falses # default case

    return (best_attribute, subtrees)

def classify(tree, input):
    """classify the input using the given decision tree"""
```

```
    # if this is a leaf node, return its value
    if tree in [True, False]:
        return tree

    # otherwise find the correct subtree
    attribute, subtree_dict = tree

    subtree_key = input.get(attribute)  # None if input is missing attribut

    if subtree_key not in subtree_dict: # if no subtree for key,
        subtree_key = None              # we'll use the None subtree

    subtree = subtree_dict[subtree_key] # choose the appropriate subtree
    return classify(subtree, input)     # and use it to classify the input

def evaluateTree(test_df, test_inputs, tree, classifycolumn, testpos, testn
    preds = []

    for i in test_inputs:
        preds.append(classify(tree, i[0]))

    prediction = pandas.DataFrame({'prediction': preds})
    test_df = test_df.join(prediction)
    test_df['evaluation'] = np.where((test_df[classifycolumn] == testneg) &
                              (test_df[classifycolumn] == testpos) & (t

    numCorrect = np.sum(test_df['evaluation'])
    numTotal = total_rows=len(test_df.axes[0])
    accuracy = numCorrect / numTotal
    incorrect_predictions = test_df[test_df.evaluation == 0]
    print("Number of correct predictions: " + str(numCorrect))
    print("Number of made predictions:  " + str(numTotal))
    print("Prediction accuracy:  " + str(accuracy*100) + "%")
    print("Incorrect predictions:  ")
    print(incorrect_predictions)
```

2.2.3 Create pandas data frame of data

In [5]:
```
import pandas
input_dfhw41 = pandas.read_table('playtennis41.txt', sep = " ")
input_dfhw41
```

Out[5]:
```
  Day   outlook temperature humidity   wind playtennis
0  d1     sunny         hot     high  False         no
1  d2     sunny         hot     high   True         no
2  d3  overcast         hot     high  False        yes
3  d4     rainy        mild     high  False        yes
```

```
4    d5      rainy     cool   normal  False   yes
5    d6      rainy     cool   normal   True    no
6    d6   overcast     cool   normal   True   yes
7    d7      sunny     mild     high  False    no
8    d8      sunny     cool   normal  False   yes
9    d9      rainy     mild   normal  False   yes
10  d10      sunny     mild   normal   True   yes
11  d11   overcast     mild     high   True   yes
12  d12   overcast      hot   normal  False   yes
13  d13      rainy     mild     high   True    no
```

2.2.4 Create inputs file. Input file is list of pairs where first element is attribute dictionary and second element is label. Then build the decision tree using ID3 method

```
In [6]: inputs_hw41 = inputformat('playtennis41.txt', delim=" ", classifycolumn = '
```

```
In [7]: tree_hw41 = build_tree_id3(inputs_hw41)
```

2.2.5 Pythonic View of Decision Tree

```
In [8]: tree_hw41
```

```
Out[8]: ('outlook',
         {None: True,
          'overcast': True,
          'rainy': ('wind', {None: True, False: True, True: False}),
          'sunny': ('humidity', {None: False, 'high': False, 'normal': True})})
```

2.2.6 Bulleted View of Decision Tree:

- Split on Outlook
  - If the outlook is overcast, always yes.
  - If the outlook is sunny, we split on humidity.
    - If humidity is High, always no.
    - If humidity is Normal, always yes.
  - If the outlook is rainy, we split on wind.
    - If wind is strong, always no.
    - If wind is weak, always yes.

2.2.7 Visual View of Decision Tree

```
            Outlook
          /    |    \
         /     |     \
        /      |      \
   Sunny  Overcast  Rainy
   /           |          \
```

```
                         /          |          \
                        /           |           \
                   Humidity         |          Wind
                    /  \            |          /   \
                   /    \           |         /     \
                  /      \          |        /       \
              High      Normal      |      True    False
               /             \      |      /           \
              /               \     |     /             \
             /                 \    |    /               \
            NO                YES  YES  NO               YES
```

2.2.8 HW4.1.1 What is the classification accuracy of the tree on the training data?

```
In [9]: evaluateTree(input_dfhw41, inputs_hw41, tree_hw41, 'playtennis', 'yes', 'nc
```

```
Number of correct predictions: 14
Number of made predictions:  14
Prediction accuracy:  100.0%
Incorrect predictions:
Empty DataFrame
Columns: [Day, outlook, temperature, humidity, wind, playtennis, prediction, evalua
Index: []
```

The tree predicts everything with perfect accuracy. This makes sense given that we're building on the entire data set (with every possibility established) and everything ends in either a true or a false.

2.2.9 HW4.1.2 Is it possible to produce some set of correct training examples that will get the algorithm to include the attribute Temperature in the learned tree, even though the true target concept is independent of Temperature? if no, explain. If yes, give such a set.

```
In [10]: %%writefile playtennis412.txt
         Day outlook temperature humidity wind playtennis
         d1 sunny hot high FALSE no
         d2 sunny hot high TRUE no
         d3 overcast hot high FALSE yes
         d4 rainy mild high FALSE yes
         d5 rainy cool normal FALSE yes
         d6 rainy cool normal TRUE no
         d6 overcast cool normal TRUE yes
         d7 sunny mild high FALSE no
         d8 sunny cool normal FALSE yes
         d9 rainy mild normal FALSE yes
```

```
Overwriting playtennis412.txt
```

```
In [11]: import pandas
         input_dfhw41 = pandas.read_table('playtennis412.txt', sep = " ")
         input_dfhw41
```

```
Out[11]:   Day   outlook temperature humidity   wind playtennis
         0  d1     sunny         hot     high  False         no
         1  d2     sunny         hot     high   True         no
         2  d3  overcast         hot     high  False        yes
         3  d4     rainy        mild     high  False        yes
         4  d5     rainy        cool   normal  False        yes
         5  d6     rainy        cool   normal   True         no
         6  d6  overcast        cool   normal   True        yes
         7  d7     sunny        mild     high  False         no
         8  d8     sunny        cool   normal  False        yes
         9  d9     rainy        mild   normal  False        yes
```

```
In [12]: inputs_hw412 = inputformat('playtennis412.txt', delim=" ", classifycolumn
```

```
In [13]: build_tree_id3(inputs_hw412)
```

```
Out[13]: ('outlook',
          {None: True,
           'overcast': True,
           'rainy': ('wind', {None: True, False: True, True: False}),
           'sunny': ('temperature',
            {None: False, 'cool': True, 'hot': False, 'mild': False})})
```

Just by trial and error form the original data set, Removing rows d10 - d12 forces temperature to be split when the outlook is sunny.

2.2.10 HW4.1.3 Now, build a tree using only examples D1–D7. What is the classification accuracy for the training set? What is the accuracy for the test set (examples D8–D14)? explain why you think these are the results.

```
In [14]: %%writefile playtennis_413train.txt
         Day outlook temperature humidity wind playtennis
         d1 sunny hot high FALSE no
         d2 sunny hot high TRUE no
         d3 overcast hot high FALSE yes
         d4 rainy mild high FALSE yes
         d5 rainy cool normal FALSE yes
         d6 rainy cool normal TRUE no
         d6 overcast cool normal TRUE yes
         d7 sunny mild high FALSE no
```

```
Overwriting playtennis_413train.txt
```

```
In [15]: %%writefile playtennis_413test.txt
         Day outlook temperature humidity wind playtennis
         d8 sunny cool normal FALSE yes
         d9 rainy mild normal FALSE yes
         d10 sunny mild normal TRUE yes
         d11 overcast mild high TRUE yes
         d12 overcast hot normal FALSE yes
         d12 rainy mild high TRUE no
```

```
Overwriting playtennis_413test.txt
```

```
In [16]: import pandas
         input_df_413train = pandas.read_table('playtennis_413train.txt', sep = " "
         input_df_413test = pandas.read_table('playtennis_413test.txt', sep = " ")
```

```
In [17]: inputs_413train = inputformat('playtennis_413train.txt', delim=" ", classi
         inputs_413test = inputformat('playtennis_413test.txt', delim=" ", classify
```

```
In [18]: tree_hw413 = build_tree_id3(inputs_413train)
         tree_hw413
```

```
Out[18]: ('outlook',
          {None: False,
           'overcast': True,
           'rainy': ('wind', {None: True, False: True, True: False}),
           'sunny': False})
```

2.2.11 Classification accuracy of training set

```
In [19]: evaluateTree(input_df_413train, inputs_413train, tree_hw413, 'playtennis',
```

```
Number of correct predictions: 8
Number of made predictions:  8
Prediction accuracy:  100.0%
Incorrect predictions:
Empty DataFrame
Columns: [Day, outlook, temperature, humidity, wind, playtennis, prediction, evalua
Index: []
```

2.2.12 Classification accuracy of test set.

```
In [20]: evaluateTree(input_df_413test, inputs_413test, tree_hw413, 'playtennis', '
```

```
Number of correct predictions: 4
Number of made predictions:  6
Prediction accuracy:  66.6666666667%
Incorrect predictions:
```

```
   Day outlook temperature humidity   wind playtennis prediction  evaluation
0   d8   sunny        cool   normal  False        yes      False           0
2  d10   sunny        mild   normal   True        yes      False           0
```

It makes sense that validating on the training set leads to perfect accuracy, because we're defining all relationships based on all training data and then testing. The reduction in accuracy on the test set is because there are new relationships in the test set that didn't exist, so the prediction becomes just a guess of what's more popular.

2.2.13 HW4.1.4 In this case, and others, there are only a few labelled examples available for training (that is, no additional data is available for testing or validation). Suggest a concrete pruning strategy, that can be readily embedded in the algorithm, to avoid over fitting. Explain why you think this strategy should work.

Build the tree to its entirety on the train set and validate against test set. Remove a node, test again. Iterate across all nodes (this is very similar to the cross validation method for regression algorithms). If any nodes decrease error, remove it. This should produce a smaller version of the tree, which by nature would reduce overfittin gof the model.

HW4.2 Regression Tree (OPTIONAL Homework)

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Implement a decision tree algorithm for regression for two input continous variables and one categorical input variable on a single core computer using Python.

- Use the IRIS dataset to evaluate your code, where the input variables are: Petal.Length Petal.Width Species and the target or output variable is Sepal.Length.
- Use the same dataset to train and test your implementation.
- Stop expanding nodes once you have less than ten (10) examples (along with the usual stopping criteria).
- Report the mean squared error for your implementation and contrast that with the MSE from scikit-learn's implementation on this dataset (http://scikit-learn.org/stable/modules/generated/sklearn.tree.DecisionTreeRegressor.html)

HW4.3 Predict survival on the Titanic using Python (Logistic regression, SVMs, Random Forests)

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The sinking of the RMS Titanic is one of the most infamous shipwrecks in history. On April 15, 1912, during her maiden voyage, the Titanic sank after colliding with an iceberg, killing 1502 out of 2224 passengers and crew. This sensational tragedy shocked the international community and led to better safety regulations for ships.

One of the reasons that the shipwreck led to such loss of life was that there were not enough lifeboats for the passengers and crew. Although there was some element of luck involved in surviving the sinking, some groups of people were more likely to survive than others, such as women, children, and the upper-class.

In this challenge, you need to review (and edit the code) in this notebook to do analysis of what sorts of people were likely to survive. In particular, please look at how the tools of machine learning are used to predict which passengers survived the tragedy. Please share any usefule graphs/analysis you come up with via the group email.

For more details see:

- https://www.kaggle.com/c/titanic

2.2.14 Pull data from Kaggle website using curl

```
In [21]: !curl -L https://www.kaggle.com/c/titanic/download/train.csv -o train.csv
```

```
  % Total    % Received % Xferd  Average Speed   Time    Time     Time  Current
                                 Dload  Upload   Total   Spent    Left  Speed
100   179  100   179    0     0    507      0 --:--:-- --:--:-- --:--:--   707
100 15343  100 15343    0     0  30638      0 --:--:-- --:--:-- --:--:-- 30638
```

2.2.15 Import necessary packages

```
In [4]: import pandas as pd
        from matplotlib import pyplot as plt
        import numpy as np
        from sklearn.ensemble import ExtraTreesClassifier
        from sklearn.feature_selection import SelectFromModel
        from sklearn.ensemble import RandomForestClassifier
        from sklearn.cross_validation import StratifiedKFold
        from sklearn.grid_search import GridSearchCV
```

```
/opt/conda/envs/python2/lib/python2.7/site-packages/matplotlib/font_manager.py:273:
  warnings.warn('Matplotlib is building the font cache using fc-list. This may take
```

2.2.16 Read in data from train set and check descriptive stats

```
In [5]: train_full = pd.read_csv('train.csv')
        train_full.describe()
```

```
/opt/conda/envs/python2/lib/python2.7/site-packages/numpy/lib/function_base.py:3403
  RuntimeWarning)
```

```
Out[5]:        PassengerId    Survived      Pclass         Age       SibSp  \
        count   891.000000  891.000000  891.000000  714.000000  891.000000
        mean    446.000000    0.383838    2.308642   29.699118    0.523008
        std     257.353842    0.486592    0.836071   14.526497    1.102743
        min       1.000000    0.000000    1.000000    0.420000    0.000000
        25%     223.500000    0.000000    2.000000         NaN    0.000000
        50%     446.000000    0.000000    3.000000         NaN    0.000000
        75%     668.500000    1.000000    3.000000         NaN    1.000000
        max     891.000000    1.000000    3.000000   80.000000    8.000000

                    Parch        Fare
        count  891.000000  891.000000
        mean     0.381594   32.204208
```

```
std       0.806057   49.693429
min       0.000000    0.000000
25%       0.000000    7.910400
50%       0.000000   14.454200
75%       0.000000   31.000000
max       6.000000  512.329200
```

2.2.17 Intuitively, Age seems important. So, rather than delete missing values, I'll replace them with a median. Median is better than mean since it is more asymptotically stable, and less impacted by outliers. Because I'll want to compare before and after, I'm keeping my train_full dataframe and creating a copy I can alter.

```
In [6]: train_changed = train_full.copy(deep=True)
```

```
In [7]: train_changed['Age'].fillna(train_changed['Age'].median(), inplace=True)
```

2.2.18 Checking again, now we have a value for all ages.

```
In [8]: train_full.describe()
```

```
Out[8]:        PassengerId    Survived      Pclass         Age       SibSp  \
        count   891.000000  891.000000  891.000000  714.000000  891.000000
        mean    446.000000    0.383838    2.308642   29.699118    0.523008
        std     257.353842    0.486592    0.836071   14.526497    1.102743
        min       1.000000    0.000000    1.000000    0.420000    0.000000
        25%     223.500000    0.000000    2.000000         NaN    0.000000
        50%     446.000000    0.000000    3.000000         NaN    0.000000
        75%     668.500000    1.000000    3.000000         NaN    1.000000
        max     891.000000    1.000000    3.000000   80.000000    8.000000

                    Parch        Fare
        count  891.000000  891.000000
        mean     0.381594   32.204208
        std      0.806057   49.693429
        min      0.000000    0.000000
        25%      0.000000    7.910400
        50%      0.000000   14.454200
        75%      0.000000   31.000000
        max      6.000000  512.329200
```

```
In [9]: train_changed.describe()
```

```
Out[9]:        PassengerId    Survived      Pclass         Age       SibSp  \
        count   891.000000  891.000000  891.000000  891.000000  891.000000
        mean    446.000000    0.383838    2.308642   29.361582    0.523008
        std     257.353842    0.486592    0.836071   13.019697    1.102743
        min       1.000000    0.000000    1.000000    0.420000    0.000000
        25%     223.500000    0.000000    2.000000   22.000000    0.000000
        50%     446.000000    0.000000    3.000000   28.000000    0.000000
```

```
75%      668.500000    1.000000    3.000000   35.000000    1.000000
max      891.000000    1.000000    3.000000   80.000000    8.000000

            Parch        Fare
count  891.000000  891.000000
mean     0.381594   32.204208
std      0.806057   49.693429
min      0.000000    0.000000
25%      0.000000    7.910400
50%      0.000000   14.454200
75%      0.000000   31.000000
max      6.000000  512.329200
```

2.2.19 Now I'll check if any other columns have missing values.

```
In [10]: len(train_changed.index) - train_changed.count()
```

```
Out[10]: PassengerId      0
         Survived         0
         Pclass           0
         Name             0
         Sex              0
         Age              0
         SibSp            0
         Parch            0
         Ticket           0
         Fare             0
         Cabin          687
         Embarked         2
         dtype: int64
```

2.2.20 Because missing Cabin is such a substantial percent of total, I'll just create a new value and group them all together. Since Embarked is missing a tiny amount, I'll remove these.

```
In [11]: train_changed['Cabin'].fillna('Missing', inplace=True)
         train_changed = train_changed.dropna()
```

2.2.21 Check one more time that no values are missing anymore.

```
In [12]: len(train_changed.index) - train_changed.count()
```

```
Out[12]: PassengerId    0
         Survived       0
         Pclass         0
         Name           0
         Sex            0
         Age            0
         SibSp          0
```

```
Parch          0
Ticket         0
Fare           0
Cabin          0
Embarked       0
dtype: int64
```

2.2.22 So, rather than delete data, we just created a new value for Cabin called 'missing' and deleted the two rows where Embarked is empty. We also substited missing Age values with the column median.

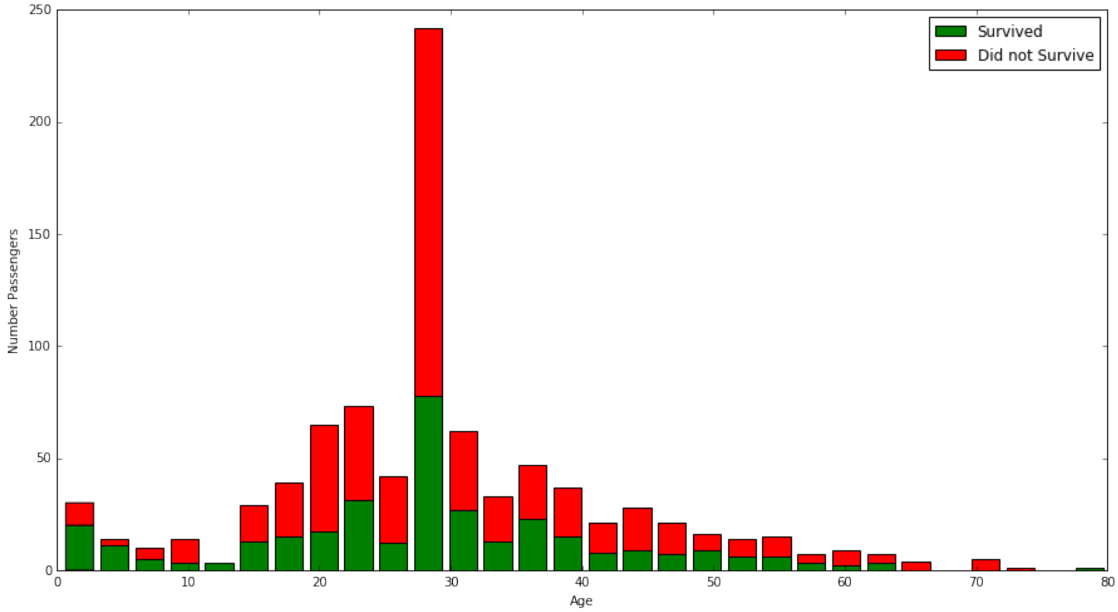
In [13]:
```
train_changed.head()
```

Out[13]:
```
   PassengerId  Survived  Pclass  \
0            1         0       3
1            2         1       1
2            3         1       3
3            4         1       1
4            5         0       3

                                                Name     Sex   Age  SibSp
0                            Braund, Mr. Owen Harris    male  22.0      1
1  Cumings, Mrs. John Bradley (Florence Briggs Th...  female  38.0      1
2                             Heikkinen, Miss. Laina  female  26.0      0
3       Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0      1
4                           Allen, Mr. William Henry    male  35.0      0

   Parch            Ticket     Fare    Cabin Embarked
0      0         A/5 21171   7.2500  Missing        S
1      0          PC 17599  71.2833      C85        C
2      0  STON/O2. 3101282   7.9250  Missing        S
3      0            113803  53.1000     C123        S
4      0            373450   8.0500  Missing        S
```

2.2.23 Now let's take a look at our data set with these replacements. First, survival based on age.

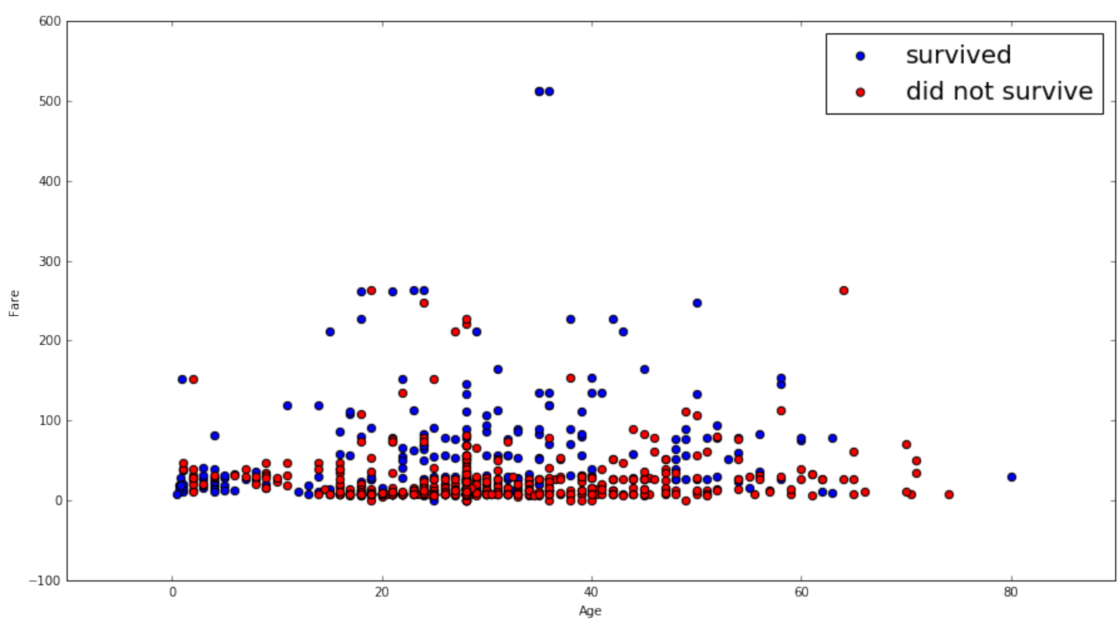
In [14]:
```
figure = plt.figure(figsize=(15,8))
plt.hist([train_changed[train_changed['Survived']==1]['Age'],train_changed
          bins = 30,label = ['Survived','Did not Survive'])
plt.xlabel('Age')
plt.ylabel('Number Passengers')
plt.legend()
```

Out[14]:
```
<matplotlib.legend.Legend at 0x7faa56566d10>
```



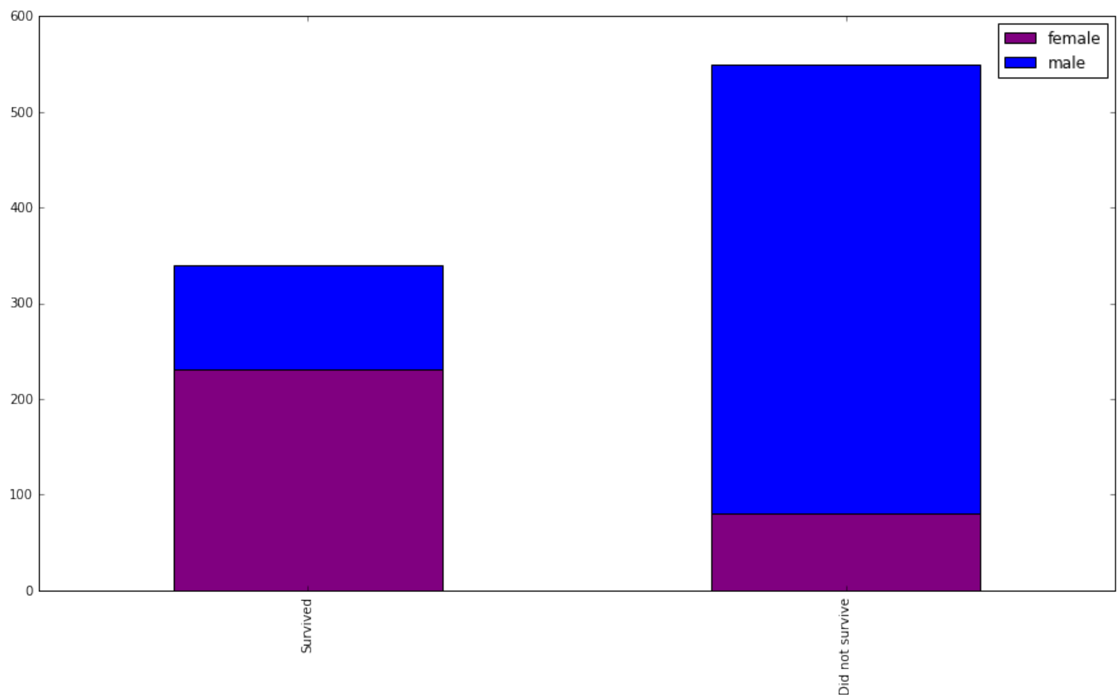

```
In [15]: plt.figure(figsize=(15,8))
         ax = plt.subplot()
         ax.scatter(train_changed[train_changed['Survived']==1]['Age'],train_change
         ax.scatter(train_changed[train_changed['Survived']==0]['Age'],train_change
         ax.set_xlabel('Age')
         ax.set_ylabel('Fare')
         ax.legend(('survived','did not survive'),scatterpoints=1,loc='upper right'
```

```
Out[15]: <matplotlib.legend.Legend at 0x7faa565b9390>
```



```
In [16]: survived_sex = train_changed[train_changed['Survived']==1]['Sex'].value_co
         dead_sex = train_changed[train_changed['Survived']==0]['Sex'].value_counts
         df = pd.DataFrame([survived_sex,dead_sex])
         df.index = ['Survived','Did not survive']
         df.plot(kind='bar',stacked=True, figsize=(15,8), color=['purple', 'blue'])
```

```
Out[16]: <matplotlib.axes._subplots.AxesSubplot at 0x7faa54329590>
```



2.2.24 Now to build a random forest decision tree. First is to create some features based on the provided attributes.

```
In [17]: # First, titles.  Create a distinct list of titles by stripping names
         # and saving prefixes.  Will use this to see if salutation has any
         # value.

         train_changed['Title'] = \
         train_changed['Name'].map(lambda name:name.split(',')[1] \
                                   .split('.')[0].strip())
         train_changed['Title'].unique()
         # array(['Mr', 'Mrs', 'Miss', 'Master', 'Don', 'Rev', 'Dr', 'Mme', 'Ms',
         #        'Major', 'Lady', 'Sir', 'Mlle', 'Col', 'Capt', 'the Countess',
         #        'Jonkheer'], dtype=object)
```

```
# Add some categorical bins.
titlesdict = {
                "Mr": "Mr", "Mrs" : "Mrs", "Miss": "Miss", "Master": "Mast
                "Dr": "Staff", "Mme": "Mrs","Ms": "Mrs","Major": "Staff",'
                "Mlle": "Miss","Col": "Staff", "Capt": "Staff", "the Count
                "Dona": "Royalty",
            }

train_changed['Title'] = train_changed.Title.map(titlesdict)

# Add title features to data set and drop Name and Title columns

titleDummies = pd.get_dummies(train_changed['Title'],prefix='Salutation')
train_changed = pd.concat([train_changed,titleDummies],axis=1)

train_changed.drop('Name',axis=1,inplace=True)
train_changed.drop('Title',axis=1,inplace=True)

# Add embark data to features and drop Embarked column
embarkedDummies = pd.get_dummies(train_changed['Embarked'],prefix='Embarke
train_changed = pd.concat([train_changed,embarkedDummies],axis=1)
train_changed.drop('Embarked',axis=1,inplace=True)

# Add Cabin data to features and drop Cabin column
train_changed['Cabin'] = train_changed['Cabin'].map(lambda c : c[0])

cabinDummies = pd.get_dummies(train_changed['Cabin'],prefix='Cabin')
train_changed = pd.concat([train_changed,cabinDummies],axis=1)
train_changed.drop('Cabin',axis=1,inplace=True)

# Now add a gender numeric binary column based on Sex and drop Sex column
train_changed['gender'] = train_changed['Sex'].map({'male': 1, 'female': (
train_changed.drop('Sex',axis=1,inplace=True)

# Add numeric value for class
pclassDummies = pd.get_dummies(train_changed['Pclass'],prefix="Pclass")
train_changed = pd.concat([train_changed,pclassDummies],axis=1)
train_changed.drop('Pclass',axis=1,inplace=True)

# Create a Family column and create values for different family sizes
train_changed['Family'] = train_changed['Parch'] + train_changed['SibSp']

train_changed['Loner'] = train_changed['Family'].map(lambda s : 1 if s ==
train_changed['SmallFam'] = train_changed['Family'].map(lambda s : 1 if 2<
train_changed['LargeFam'] = train_changed['Family'].map(lambda s : 1 if 6<
train_changed.drop('Family',axis=1,inplace=True)
```

```
        # Drop Ticket column
        train_changed.drop('Ticket',axis=1,inplace=True)

        # Now show rows and columns.
        train_changed.shape
```

```
Out[17]: (889, 31)
```

2.2.25 I now have 889 rows and 31 features. I now will split the data into test and train sets.

```
In [18]: # Finally, create an array of actuals, then create random generated list o
         # 75% split vs 25% split

         separator = np.random.rand(len(train_changed)) < 0.80

In [19]: train = train_changed[separator]

In [20]: test = train_changed[~separator]
```

2.2.26 Now make sure train and test sets have been successfully created by checking row counts.

```
In [21]: print("Train set has " + str(len(train)) + " rows.")
         print("Test set has " + str(len(test)) + " rows.")

Train set has 724 rows.
Test set has 165 rows.
```

2.2.27 Before starting the model, normalize the data by dividing each cell by the column max.

```
In [22]: features = list(train.columns)
         features.remove('PassengerId')
         train[features] = train[features].apply(lambda x: x/x.max(), axis=0)

/opt/conda/envs/python2/lib/python2.7/site-packages/pandas/core/frame.py:2378: Sett
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/i
  self[k1] = value[k2]
```

2.2.28 Compute feature importance on train_changed set.

```
In [23]: trainActs = train.Survived
         train.drop('Survived', axis=1, inplace=True)
```

```
/opt/conda/envs/python2/lib/python2.7/site-packages/ipykernel/__main__.py:2: Settin
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/i
  from ipykernel import kernelapp as app
```

```
In [24]: testActs = test.Survived
         test.drop('Survived', axis=1, inplace=True)
```

```
/opt/conda/envs/python2/lib/python2.7/site-packages/ipykernel/__main__.py:2: Settin
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/i
  from ipykernel import kernelapp as app
```

```
In [25]: etc = ExtraTreesClassifier(n_estimators=200)
         etc = etc.fit(train, trainActs)
```

```
In [26]: features = pd.DataFrame()
         features['feature'] = train.columns
         features['importance'] = etc.feature_importances_
```

```
In [27]: features.sort(['importance'],ascending=False)
```

```
/opt/conda/envs/python2/lib/python2.7/site-packages/ipykernel/__main__.py:1: Future
  if __name__ == '__main__':
```

Out[27]:

	feature	importance
0	PassengerId	0.150979
1	Age	0.134375
4	Fare	0.130803
23	gender	0.114050
7	Salutation_Mr	0.108358
26	Pclass_3	0.042242
8	Salutation_Mrs	0.035611
6	Salutation_Miss	0.033582
21	Cabin_M	0.027720
2	SibSp	0.025162
24	Pclass_1	0.023742
3	Parch	0.019626
28	SmallFam	0.019548
13	Embarked_S	0.017537
5	Salutation_Master	0.015171
29	LargeFam	0.014837
11	Embarked_C	0.014042
25	Pclass_2	0.012618

```
27                Loner    0.010352
10    Salutation_Staff    0.009686
18              Cabin_E    0.008261
12          Embarked_Q    0.008030
16              Cabin_C    0.005766
15              Cabin_B    0.005729
17              Cabin_D    0.005373
14              Cabin_A    0.002308
19              Cabin_F    0.001874
20              Cabin_G    0.001577
9   Salutation_Royalty    0.000609
22              Cabin_T    0.000434
```

In [28]:
```python
model = SelectFromModel(etc, prefit=True)
train_new = model.transform(train)
train_new.shape
```

Out[28]:
```
(724, 8)
```

In [29]:
```python
test_new = model.transform(test)
test_new.shape
```

Out[29]:
```
(165, 8)
```

2.2.29 We're now down to 8 features to select from to build our tree. Now, to tune the random forest hyperparameters.

In [30]:
```python
rfc = RandomForestClassifier(max_features='sqrt')

params = {
                 'max_depth' : [1,2,3,4,5,6,7,8,9,10],
                 'n_estimators': [50,100,150,200,250,300,350,400,450,500],
                 'criterion': ['entropy']
                 }

cv = StratifiedKFold(trainActs, n_folds=10)

grid_search = GridSearchCV(rfc,
                           param_grid=params,
                           cv=cv)

grid_search.fit(train_new, trainActs)

print('Best score: {}'.format(grid_search.best_score_))
print('Best parameters: {}'.format(grid_search.best_params_))
```

```
Best score: 0.825966850829
Best parameters: {'n_estimators': 150, 'criterion': 'entropy', 'max_depth': 9}
```

2.2.30 Now to use the above tuned hyperparameters.

```
In [31]: output = grid_search.predict(test_new).astype(int)
         df_output = pd.DataFrame()
         df_output['PassengerId'] = test['PassengerId']
         df_output['Preds'] = output
         df_output.sort('PassengerId')
```

```
/opt/conda/envs/python2/lib/python2.7/site-packages/ipykernel/__main__.py:5: Future
```

```
Out[31]:      PassengerId  Preds
         3              4      1
         4              5      0
         8              9      1
         9             10      1
         27            28      0
         30            31      0
         32            33      1
         40            41      1
         49            50      1
         54            55      0
         58            59      1
         71            72      1
         84            85      1
         85            86      1
         99           100      0
         104          105      0
         106          107      0
         111          112      0
         124          125      0
         127          128      0
         128          129      0
         130          131      0
         133          134      1
         137          138      0
         141          142      0
         146          147      0
         147          148      0
         154          155      0
         176          177      0
         182          183      0
         ..           ...    ...
         739          740      0
         740          741      1
         741          742      1
         751          752      0
         756          757      0
         760          761      0
```

```
769          770      0
778          779      0
782          783      1
786          787      0
793          794      1
808          809      1
814          815      0
815          816      0
817          818      1
821          822      0
823          824      0
837          838      0
840          841      0
854          855      1
857          858      0
858          859      0
867          868      0
871          872      1
874          875      1
878          879      0
882          883      0
887          888      1
888          889      0
889          890      0

[165 rows x 2 columns]
```

```
In [32]: test['Survived'] = testActs
```

```
/opt/conda/envs/python2/lib/python2.7/site-packages/ipykernel/__main__.py:1: Settin
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/i
  if __name__ == '__main__':
```

2.2.31 Finally to determine the accuracy of the model

```
In [33]: test_acc = pd.merge(test, df_output, how='inner', on='PassengerId')

         cols = [col for col in test_acc.columns if col in ['PassengerId', 'Survive

         test_acc_fin = test_acc[cols]
```

```
In [34]: test_acc_fin['Matches'] =(((test_acc_fin['Survived'] == 1)&(test_acc_fin['
```

```
/opt/conda/envs/python2/lib/python2.7/site-packages/ipykernel/__main__.py:1: Settin
A value is trying to be set on a copy of a slice from a DataFrame.
```

```
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/i
  if __name__ == '__main__':
```

```
In [35]: numCorrect = np.sum(test_acc_fin['Matches'])
         numTotal = total_rows=len(test_acc_fin.axes[0])
         accuracy = float(numCorrect) / numTotal

         print("Number of correct predictions: " + str(numCorrect))
         print("Number of made predictions:  " + str(numTotal))
         print("Accuracy rate of:  " + str(accuracy*100)+'%')
```

```
Number of correct predictions: 127
Number of made predictions:  165
Accuracy rate of:  76.9696969697%
```

HW4.4 Heritage Healthcare Prize (Predict # Days in Hospital next year) Back to Table of Contents

1. Introduction Back to Table of Contents

The Heritage Health Prize (HHP) was a data science challenge sponsored by The Heritage Provider Network. It took place from April 4, 2011 to April 4, 2013. For information on the winning entries, please see here.

Please see the following notebooks for more background and candidate solutions

- Spark Map-Reduce + MMLlib solution (with optional extensions) See Notebook
- Spark SQL + MLLib solution (with optional extensions): Notebook

Please look at section 7 in both notebooks complete any one or more the suggested next steps. E.g.,

- Please complete the EDA extensions using inspiration from the Titanic Notebook from above.
- **Complete Section 3.B: EDA-0. Gather information to see what transformations may need to be done on the data.** Answer questions about each raw DataFrame. In general, is the data in good shape? For example, in each of the Target DataFrames (df_target_Y1, df_target_Y2, df_target_Y3), what values does DaysInHospital take on? Are they all integers? What values does ClaimsTruncated take on? Are they all integers? In the Claims DataFrame (df_claims), how many different ProviderIDs are there? How many different PrimaryConditionGroups are there? What are their values? What values can the CharlesonIndex take on? Are they integers? In the Drug Count DataFrame (df_drug_count), what values can DrugCount take on? Are they all integers? Given this information, what transformations are needed?

- **Complete Section 3.D: EDA-1. Create tables and graphs to display information about the transformed DataFrames.** For inspiration, see the Titanic notebook discussed above. Answer questions about each DataFrame. For example, in each of the Target DataFrames (df_target_Y1, df_target_Y2, df_target_Y3), what is the minimum, maximum, mean, and standard deviation of DaysInHospital? In the Claims DataFrame, group by MemberID and Year and count the number of records. What is the minimum, maximum, mean, and standard deviation of the count? Do the same for the Drug Count and Lab Count DataFrames, etc.
- __ Please generate ensemble of DT model using 100 trees with 8 nodes and report the Loss __ Try additional models. See possibilities here (e.g. Decision Tree Regressor, Gradient-Boosted Trees Regressor, Random Forest Regressor). See an example here. Tune their hyperparameters. Try different feature selections. Try a two-step model.

2.3 Homework is in these Git pages.

Map-Reduce: https://github.com/zuehlkescott5/MachineLearning/blob/master/TargetDataScienceTraining/W
Map-Reduce%20SZ.ipynb

SQL(noclaims): https://github.com/zuehlkescott5/MachineLearning/blob/master/TargetDataScienceTrain

SQL(claims): https://github.com/zuehlkescott5/MachineLearning/blob/master/TargetDataScienceTraining

```
In [ ]:
```