State Farm Classification Coding Exercise

Part 1 - Training Data Set Exploratory Data Analysis and Feature Engineering

A. Import Libraries and Training Data Set, and Check for Missing Values

Import numpy and pandas.

In [1]:
```
import numpy as np
import pandas as pd
```

Import data visualization libraries and set %matplotlib inline.

In [2]:
```
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

Import Exercise 2 training data set comma-separated (CSV) file into a Pandas dataframe.

In [3]:
```
train = pd.read_csv('../State_Farm/Data/exercise_02_train.csv', sep=',')
```

Create copy of training dataframe for exploratory data analysis and feature engineering.

In [4]:
```
train1 = train.copy()
```

View first five rows of training dataframe.

In [5]:
```
train1.head()
```

Out[5]:

	x0	x1	x2	x3	x4	x5	x6	x7	
0	0.198560	74.425320	67.627745	-3.095111	-6.822327	19.048071	-0.362378	-10.699174	-22.69
1	-29.662621	24.320711	-48.205182	1.430339	-6.552206	4.263074	6.551412	4.265483	1.24
2	15.493759	-66.160459	50.512903	-2.265792	14.428578	2.509323	-6.707536	3.820842	-11.10
3	-19.837651	33.210943	53.405563	1.079462	11.364251	-1.064581	9.308857	9.266076	14.55
4	11.896655	-26.717872	-17.758176	1.692017	21.553537	-5.852097	-0.857435	-2.186940	18.07

5 rows × 101 columns

Obtain number of rows and columns in training dataframe.

In [6]:
```
train1.shape
```

Out[6]: (40000, 101)

Check for presence of missing values for all features.

In [7]:
```
train1.isnull().sum().sort_values(ascending=False)
```

Out[7]:
```
x96    15
x63    14
x13    14
x18    14
x85    14
x24    14
x62    13
x35    13
x21    13
x69    13
x97    13
x99    13
x42    12
x60    12
x65    12
x73    12
x17    12
x25    11
x51    11
x56    11
x0     11
x55    11
x89    11
x12    11
x86    11
x28    11
x76    10
x75    10
x48    10
x1     10
       ..
x98     6
x5      6
x8      6
x22     6
x79     6
x53     6
x83     5
x20     5
x71     5
x70     5
x64     5
x54     5
x45     5
x29     5
x37     4
x41     4
x91     4
x32     4
x88     4
x30     4
x87     4
x81     4
x47     4
```

```
x15     4
x84     3
x14     3
x49     3
x44     2
x43     2
y       0
Length: 101, dtype: int64
```

B. Explore and Engineer Numerical Features

Identify which training data set features are categorical.

In [8]:
```
train1.select_dtypes(exclude=['int64', 'float']).columns
```

Out[8]:
```
Index(['x34', 'x35', 'x41', 'x45', 'x68', 'x93'], dtype='object')
```

Check that the data types for all numerical features are float64.

In [9]:
```
num_features = train1.columns.difference(['y', 'x34', 'x35', 'x41', 'x45', 'x68',
```

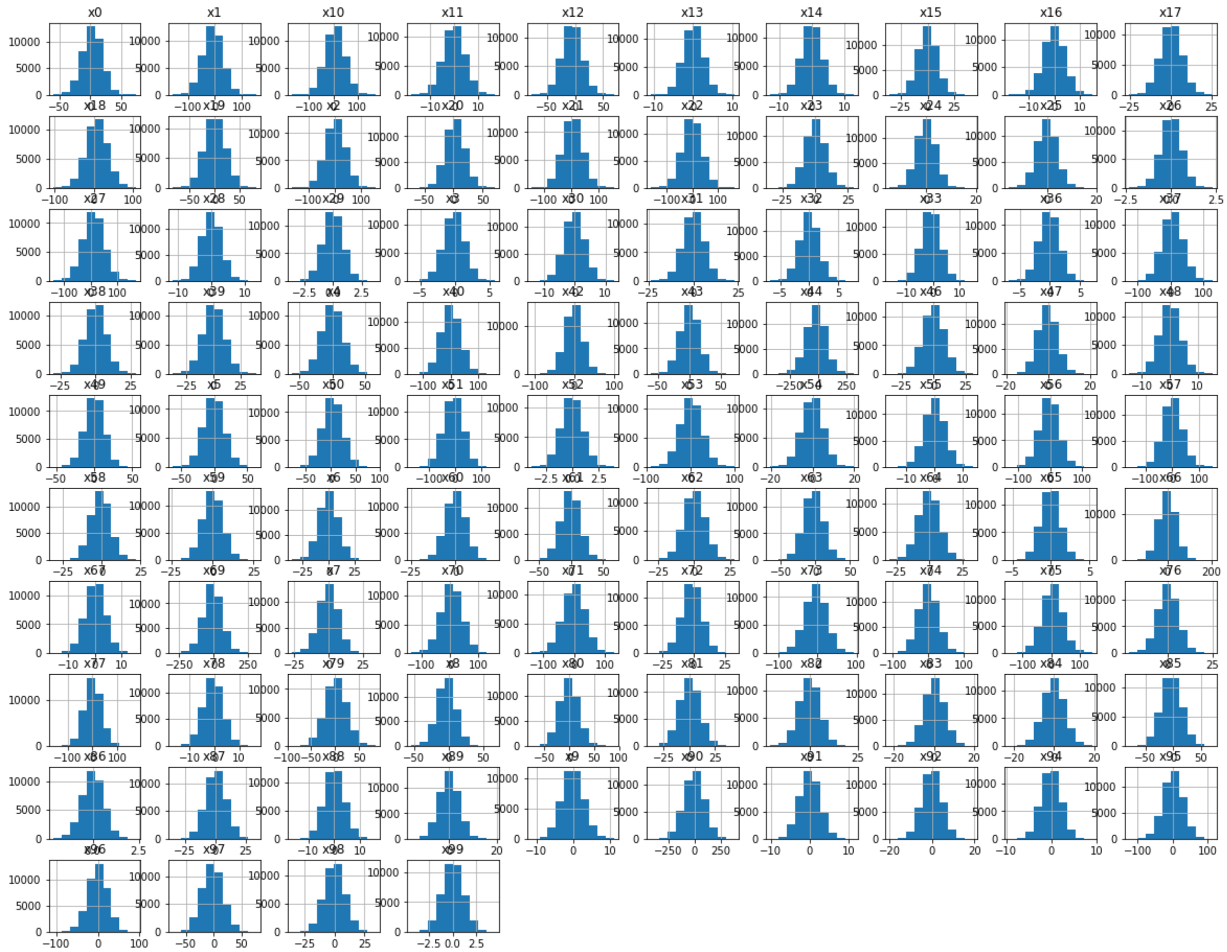
In [10]:
```
train1[num_features].info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 40000 entries, 0 to 39999
Data columns (total 94 columns):
x0     39989 non-null float64
x1     39990 non-null float64
x10    39991 non-null float64
x11    39993 non-null float64
x12    39989 non-null float64
x13    39986 non-null float64
x14    39997 non-null float64
x15    39996 non-null float64
x16    39993 non-null float64
x17    39988 non-null float64
x18    39986 non-null float64
x19    39992 non-null float64
x2     39992 non-null float64
x20    39995 non-null float64
x21    39987 non-null float64
x22    39994 non-null float64
x23    39992 non-null float64
x24    39986 non-null float64
x25    39989 non-null float64
x26    39991 non-null float64
x27    39992 non-null float64
x28    39989 non-null float64
x29    39995 non-null float64
x3     39991 non-null float64
x30    39996 non-null float64
x31    39992 non-null float64
x32    39996 non-null float64
x33    39990 non-null float64
x36    39993 non-null float64
x37    39996 non-null float64
x38    39994 non-null float64
x39    39991 non-null float64
x4     39992 non-null float64
x40    39994 non-null float64
x42    39988 non-null float64
x43    39998 non-null float64
x44    39998 non-null float64
x46    39993 non-null float64
x47    39996 non-null float64
x48    39990 non-null float64
x49    39997 non-null float64
x5     39994 non-null float64
x50    39993 non-null float64
x51    39989 non-null float64
x52    39992 non-null float64
x53    39994 non-null float64
x54    39995 non-null float64
x55    39989 non-null float64
x56    39989 non-null float64
x57    39992 non-null float64
x58    39991 non-null float64
```

```
x59    39990 non-null float64
x6     39990 non-null float64
x60    39988 non-null float64
x61    39993 non-null float64
x62    39987 non-null float64
x63    39986 non-null float64
x64    39995 non-null float64
x65    39988 non-null float64
x66    39991 non-null float64
x67    39991 non-null float64
x69    39987 non-null float64
x7     39991 non-null float64
x70    39995 non-null float64
x71    39995 non-null float64
x72    39992 non-null float64
x73    39988 non-null float64
x74    39993 non-null float64
x75    39990 non-null float64
x76    39990 non-null float64
x77    39991 non-null float64
x78    39993 non-null float64
x79    39994 non-null float64
x8     39994 non-null float64
x80    39991 non-null float64
x81    39996 non-null float64
x82    39992 non-null float64
x83    39995 non-null float64
x84    39997 non-null float64
x85    39986 non-null float64
x86    39989 non-null float64
x87    39996 non-null float64
x88    39996 non-null float64
x89    39989 non-null float64
x9     39993 non-null float64
x90    39993 non-null float64
x91    39996 non-null float64
x92    39993 non-null float64
x94    39992 non-null float64
x95    39992 non-null float64
x96    39985 non-null float64
x97    39987 non-null float64
x98    39994 non-null float64
x99    39987 non-null float64
dtypes: float64(94)
memory usage: 28.7 MB
```

View scatter matrix of numerical features to inspect their distributions.

In [11]:
```
train1[num_features].hist(figsize=(20,16));
```



- All the numerical features are normally distributed. The number of missing values for each feature ranges from 2 to 15 while the total number of rows in the training data set is 40,000. Given these conditions, I decided to impute the missing values with the mean of the feature.

Impute missing values in numerical features with mean.

In [12]:
```
train2 = train1.fillna(train1[num_features].mean())
```

Check numerical features for any missing values.

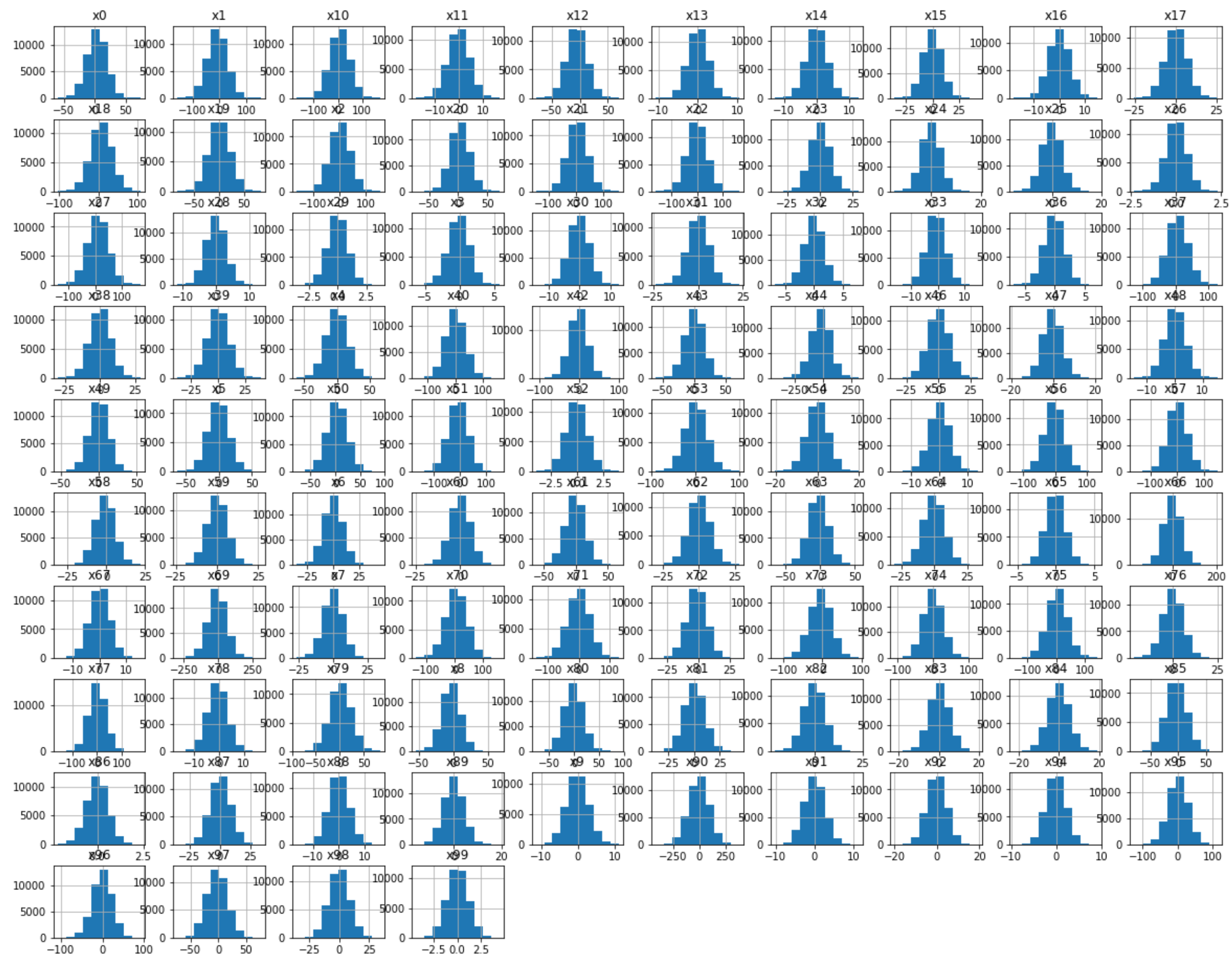
In [13]:
```
train2[num_features].isnull().sum().sort_values(ascending=False)
```

Out[13]:
```
x99    0
x42    0
x31    0
x32    0
x33    0
x36    0
x37    0
x38    0
x39    0
x4     0
x40    0
x43    0
x3     0
x44    0
x46    0
x47    0
x48    0
x49    0
x5     0
x50    0
x51    0
x52    0
x30    0
x29    0
x98    0
x18    0
x1     0
x10    0
x11    0
x12    0
      ..
x91    0
x92    0
x94    0
x95    0
x96    0
x97    0
x78    0
x77    0
x76    0
x75    0
x57    0
x58    0
x59    0
x6     0
x60    0
x61    0
x62    0
x63    0
x64    0
x65    0
x66    0
x67    0
x69    0
```

```
x7      0
x70     0
x71     0
x72     0
x73     0
x74     0
x0      0
Length: 94, dtype: int64
```

View scatter matrix of imputed numerical features to check if the mean imputations skewed their distributions.

In [14]:
```
train2[num_features].hist(figsize=(20,16));
```



- The histograms for all the numerical features show that their distributions still continue to remain normal after imputing their missing values with the mean.

C. Explore and Engineer Categorical Features

Check categorical feature data types.

In [15]:
```
cat_features1 = ['y', 'x34', 'x35', 'x41', 'x45', 'x68', 'x93']
```

In [16]:
```
train2[cat_features1].info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 40000 entries, 0 to 39999
Data columns (total 7 columns):
y      40000 non-null int64
x34    39993 non-null object
x35    39987 non-null object
x41    39996 non-null object
x45    39995 non-null object
x68    39992 non-null object
x93    39993 non-null object
dtypes: int64(1), object(6)
memory usage: 2.1+ MB
```

View summary statistics for categorical features.

In [17]:
```
train2.describe(include=['object'])
```

Out[17]:

	x34	x35	x41	x45	x68	x93
count	39993	39987	39996	39995	39992	39993
unique	10	8	37863	10	12	3
top	volkswagon	wed	$-712.34	-0.01%	July	asia
freq	12455	14793	4	9578	11080	35416

Convert currency and percent string features (x41 and x45) to float data type.

In [18]:
```
train2[['x41_flt']] = train2[['x41']].apply(lambda x: x.str.replace('$','')).asty
train2[['x45_pct']] = train2[['x45']].apply(lambda x: x.str.replace('%','')).asty
train3 = train2.drop(['x41', 'x45'], axis=1)
```

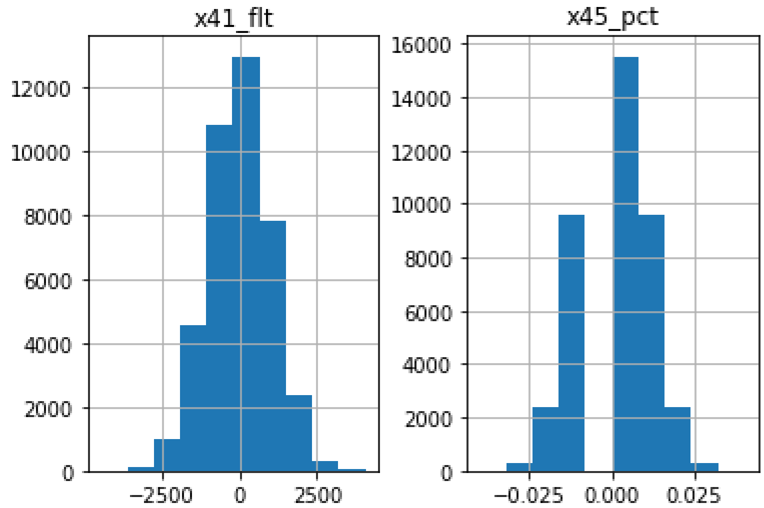
Check the number of missing values for the numerical x41 and x45 features.

In [19]:
```
train3[['x41_flt', 'x45_pct']].isnull().sum()
```

Out[19]:
```
x41_flt    4
x45_pct    5
dtype: int64
```

View scatter matrix of numerical x41 and x45 features to inspect their distributions.

In [20]:
```
train3[['x41_flt', 'x45_pct']].hist();
```



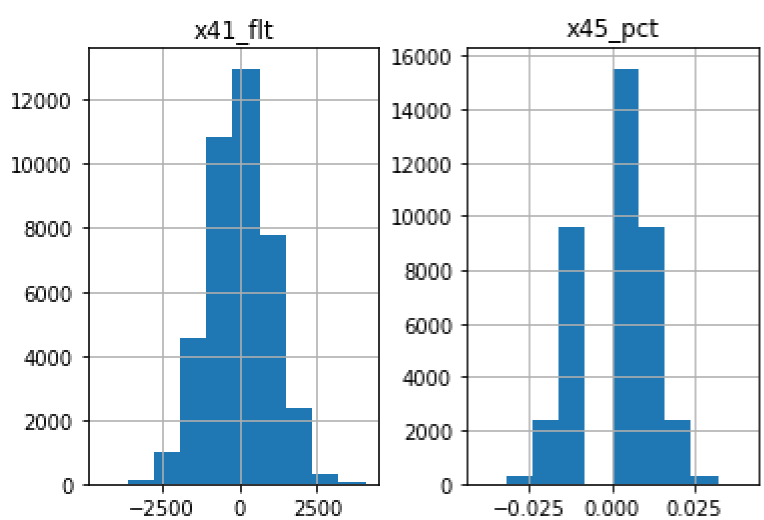
- The numerical x41 and x45 features are normally distributed. The number of missing values for the numerical x41 and x45 features is 4 and 5, respectively. Again, the total number of rows in the training data set is 40,000. Given these conditions, I decided to impute the missing values with the mean of the feature.

Impute missing values in numerical x41 and x45 features with mean.

In [21]:
```
train4 = train3.fillna(train3[['x41_flt', 'x45_pct']].mean())
```

View scatter matrix of imputed numerical x41 and x45 features to check if the mean imputations skewed their distributions.

In [22]:
```
train4[['x41_flt', 'x45_pct']].hist();
```



- The histograms for the numerical x41 and x45 features show that their distributions still continue to remain normal after imputing their missing values with the mean.

Check for features that still have missing values.

In [23]:
```
train4.isnull().sum().sort_values(ascending=False).head()
```

Out[23]:
```
x35        13
x68         8
x93         7
x34         7
x45_pct     0
dtype: int64
```

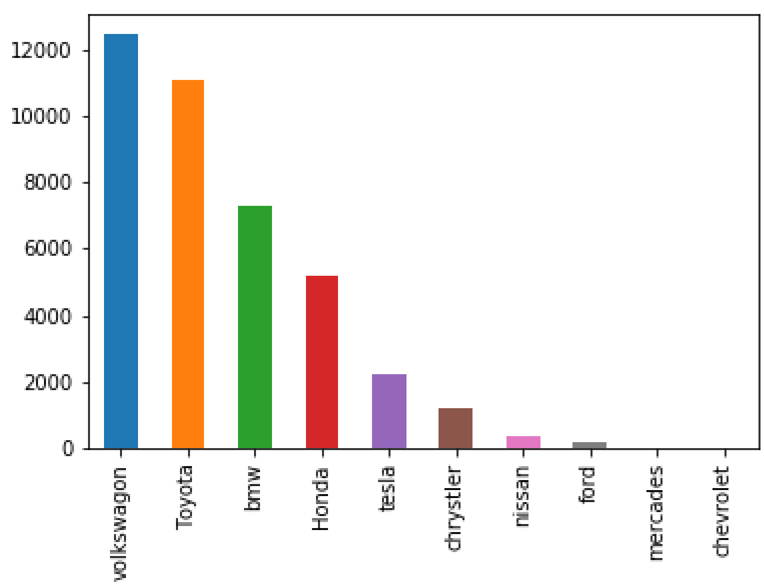
Identify remaining categorical features.

In [24]:
```
train4.select_dtypes(exclude=['int64', 'float']).columns
```

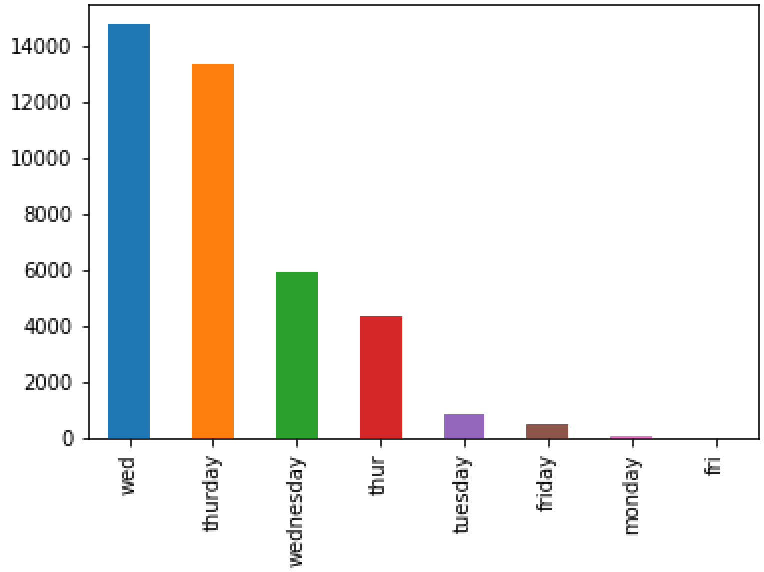
Out[24]:
```
Index(['x34', 'x35', 'x68', 'x93'], dtype='object')
```

View bar plots for categorical features of x34, x35, x68, and x93.

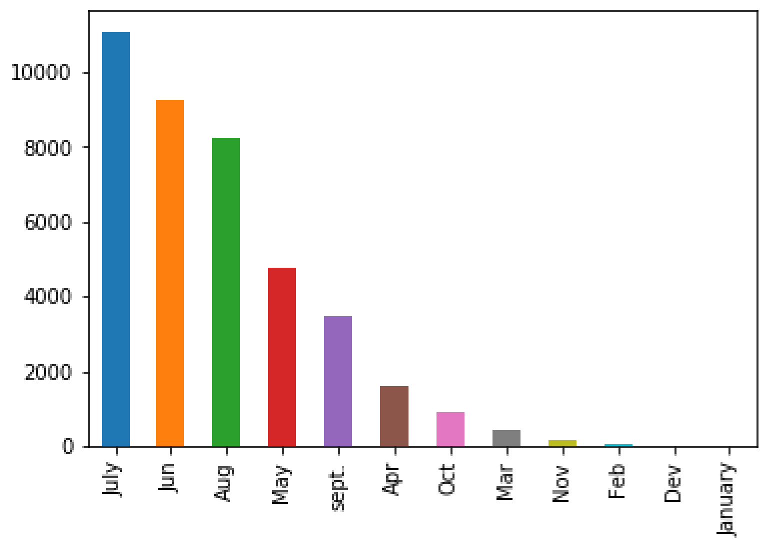
In [25]:
```
train4.x34.value_counts().plot(kind='bar');
```



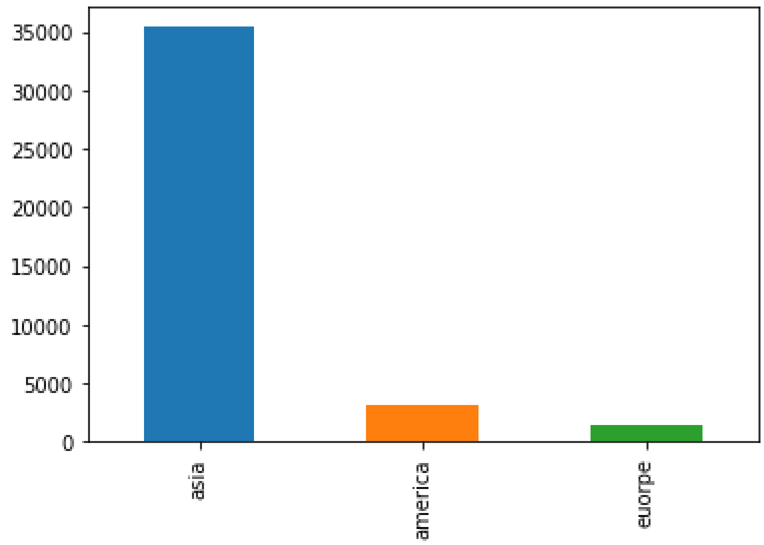
In [26]:
```
train4.x35.value_counts().plot(kind='bar');
```



In [27]:
```
train4.x68.value_counts().plot(kind='bar');
```



In [28]:
```
train4.x93.value_counts().plot(kind='bar');
```



- The missing values for the categorical features of x34, x35, x68, and x93 are truly blank. In other words, much more domain knowledge is required to impute these missing values. Going forward, I will assign these missing values their own missing category.

Replace all categorical feature missing values with their own missing category.

In [29]:
```
train4['x34'] = train4.x34.fillna('No_Car_Make')
train4['x35'] = train4.x35.fillna('No_Weekday')
train4['x68'] = train4.x68.fillna('No_Month')
train4['x93'] = train4.x93.fillna('No_Continent')
```

Check that all categorical features have zero missing values.

In [30]:
```
train4[['x34', 'x35', 'x68', 'x93']].isnull().sum().sort_values(ascending=False)
```

Out[30]:
```
x93    0
x68    0
x35    0
x34    0
dtype: int64
```

Obtain value counts and y target feature probabilities for each x34 category.

In [31]:
```
train4.groupby('x34').y.agg(['count', 'mean']).sort_values('mean', ascending=Fals
```

Out[31]:

x34	count	mean
ford	159	0.220126
Toyota	11079	0.204982
volkswagon	12455	0.204978
Honda	5179	0.204093
bmw	7282	0.203241
nissan	334	0.200599
tesla	2248	0.194840
chrystler	1219	0.194422
mercades	27	0.148148
No_Car_Make	7	0.142857
chevrolet	11	0.090909

Clean x34 feature car make names, and obtain value counts and y target feature probabilities again.

In [32]:
```
train4['x34'] = train4.x34.map({'ford':'Ford', 'Toyota':'Toyota', 'volkswagon':'V
                                'nissan':'Nissan', 'tesla':'Tesla', 'chrystler':'
                                'No_Car_Make':'No_Car_Make', 'chevrolet':'Chevrol
train4.groupby('x34').y.agg(['count', 'mean']).sort_values('mean', ascending=Fals
```

Out[32]:

x34	count	mean
Ford	159	0.220126
Toyota	11079	0.204982
Volkswagen	12455	0.204978
Honda	5179	0.204093
BMW	7282	0.203241
Nissan	334	0.200599
Tesla	2248	0.194840
Chrysler	1219	0.194422
Mercedes	27	0.148148
No_Car_Make	7	0.142857
Chevrolet	11	0.090909

Create x34 dummy features with Volkswagen as reference category and add it to training

dataframe.

In [33]:
```
x34_dummies = pd.get_dummies(train4.x34).drop('Volkswagen', axis=1)
train5 = pd.concat([train4, x34_dummies], axis=1)
```

Obtain value counts and y target feature probabilities for each x35 category.

In [34]:
```
train5.groupby('x35').y.agg(['count', 'mean']).sort_values('mean', ascending=Fals
```

Out[34]:

x35	count	mean
monday	61	0.426230
tuesday	894	0.347875
fri	24	0.291667
wednesday	5920	0.256757
wed	14793	0.211789
thurday	13375	0.174430
thur	4383	0.165184
friday	537	0.163873
No_Weekday	13	0.153846

Clean x35 feature weekday names, and obtain value counts and y target feature probabilities again.

In [35]:
```
train5['x35'] = train5.x35.map({'monday':'Monday', 'tuesday':'Tuesday', 'fri':'Fr
                                'wed':'Wednesday', 'thurday':'Thursday', 'thur':'
                                'No_Weekday':'No_Weekday'})
train5.groupby('x35').y.agg(['count', 'mean']).sort_values('mean', ascending=Fals
```

Out[35]:

x35	count	mean
Monday	61	0.426230
Tuesday	894	0.347875
Wednesday	20713	0.224642
Thursday	17758	0.172148
Friday	561	0.169340
No_Weekday	13	0.153846

Create x35 dummy features with Wednesday as reference category and add it to training dataframe.

In [36]:
```
x35_dummies = pd.get_dummies(train5.x35).drop('Wednesday', axis=1)
train6 = pd.concat([train5, x35_dummies], axis=1)
```

Obtain value counts and y target feature probabilities for each x68 category.

In [37]:
```
train6.groupby('x68').y.agg(['count', 'mean']).sort_values('mean', ascending=Fals
```

Out[37]:

x68	count	mean
Dev	20	0.450000
Feb	56	0.446429
Nov	151	0.377483
January	10	0.300000
Mar	431	0.278422
Oct	904	0.264381
Apr	1614	0.258984
May	4769	0.214930
sept.	3485	0.212052
Jun	9261	0.194795
Aug	8211	0.193034
July	11080	0.191336
No_Month	8	0.000000

Clean x68 feature month names, and obtain value counts and y target feature probabilities again.

In [38]:
```
train6['x68'] = train6.x68.map({'Dev':'December', 'Feb':'February', 'Nov':'Novemb
                                 'Oct':'October', 'Apr':'April', 'May':'May', 'sep
                                 'July':'July', 'No_Month':'No_Month'})
train6.groupby('x68').y.agg(['count', 'mean']).sort_values('mean', ascending=Fals
```

Out[38]:

x68	count	mean
December	20	0.450000
February	56	0.446429
November	151	0.377483
January	10	0.300000
March	431	0.278422
October	904	0.264381
April	1614	0.258984
May	4769	0.214930
September	3485	0.212052
June	9261	0.194795
August	8211	0.193034
July	11080	0.191336
No_Month	8	0.000000

Create x68 dummy features with July as reference category and add it to training dataframe.

In [39]:
```
x68_dummies = pd.get_dummies(train6.x68).drop('July', axis=1)
train7 = pd.concat([train6, x68_dummies], axis=1)
```

Obtain value counts and y target feature probabilities for each x93 category.

In [40]:
```
train7.groupby('x93').y.agg(['count', 'mean']).sort_values('mean', ascending=Fals
```

Out[40]:

x93	count	mean
No_Continent	7	0.285714
america	3131	0.217183
asia	35416	0.202761
euorpe	1446	0.194329

Clean x93 feature continent names, and obtain value counts and y target feature probabilities again.

In [41]:
```
train7['x93'] = train7.x93.map({'No_Continent':'No_Continent', 'america':'America
train7.groupby('x93').y.agg(['count', 'mean']).sort_values('mean', ascending=Fals
```

Out[41]:

x93	count	mean
No_Continent	7	0.285714
America	3131	0.217183
Asia	35416	0.202761
Europe	1446	0.194329

Create x93 dummy features with Asia as reference category and add it to training dataframe.

In [42]:
```
x93_dummies = pd.get_dummies(train7.x93).drop('Asia', axis=1)
train8 = pd.concat([train7, x93_dummies], axis=1)
```

D. Finalize and Export Cleaned Training Data Set for Export

Drop categorical features from training dataframe.

In [43]:
```
train_cleaned = train8.drop(['x34', 'x35', 'x68', 'x93'], axis=1)
```

Obtain number of rows and columns in training dataframe with engineered and cleaned features.

In [44]:
```
train_cleaned.shape
```

Out[44]:
```
(40000, 127)
```

Check for any remaining missing values in training dataframe with engineered and cleaned features.

In [45]:
```
train_cleaned.isnull().sum().sort_values(ascending=False)
```

Out[45]:
```
No_Continent    0
x50             0
x33             0
x36             0
x37             0
x38             0
x39             0
x40             0
x42             0
x43             0
x44             0
x46             0
x47             0
x48             0
x49             0
x51             0
x31             0
x52             0
x53             0
x54             0
x55             0
x56             0
x57             0
x58             0
x59             0
x60             0
x61             0
x62             0
x63             0
x64             0
               ..
x83             0
x70             0
x71             0
x72             0
x73             0
x74             0
x75             0
x76             0
x77             0
x78             0
x79             0
x80             0
x81             0
x82             0
x84             0
x99             0
x85             0
x86             0
x87             0
x88             0
x89             0
x90             0
x91             0
```

```
x92           0
x94           0
x95           0
x96           0
x97           0
x98           0
x0            0
Length: 127, dtype: int64
```

Export training dataframe with engineered and cleaned features to CSV file.

In [46]:
```
train_cleaned.to_csv('../State_Farm/Data/train_cleaned.csv', sep=',', index=False
```

Save training dataframe with engineered and cleaned features to pickle file for subsequent feature selection notebook.

In [47]:
```
train_cleaned.to_pickle('../State_Farm/Data/train_cleaned.pickle')
```