```
In [5]: import pandas as pd ## for creating dataframe
import numpy as np ## array manupulation
```

In [6]: df=pd.read_csv('data_re.csv') ## read thedata and create a dataframe

In [7]: ###ok before go into the machine learning algorithm
clean the data

In [8]: df.head() ## peak of the data from the head side

Out[8]:

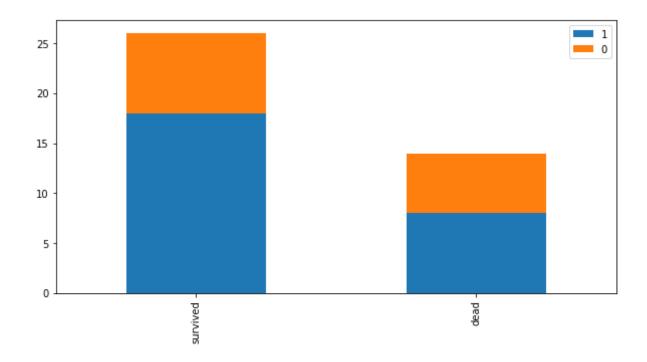
	Date	Spot	Types of road	Injured	Death	How	Insane	Addicted	Unathorized
0	May 01,2018	Hatirjheel, Dhaka	1	0	2	Motorcycle skidded off the road after hitting	1	1	0
1	June 28,2017	Kalapani,Guimara, Khagrachari	2	10	3	After skidded off the road the bus hit the tree.	1	0	0
2	February 23,2018	Mymensingh road	2	25	4	bus felt into Roadside ditch	1	0	0
3	February 7,2018	Sunamganj pagla bazar	2	0	4	bus and private car collision	0	0	1
4	December 18,2018	Gazipur sarak	3	2	1	bus thrush rickshaw	1	0	0

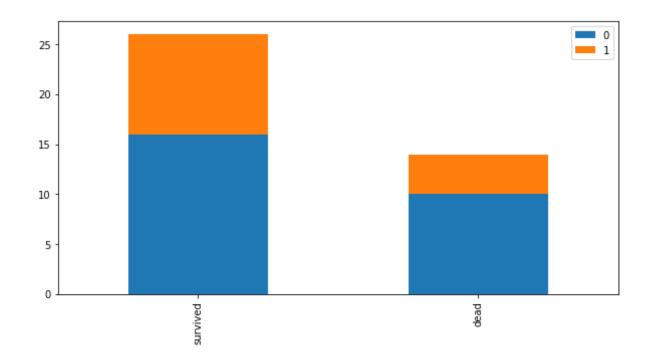
5 rows × 23 columns

```
In [9]: df.tail() ### data from tail side
 Out[9]:
                                     Types
                   Date
                                Spot
                                        of Injured Death How Insane Addicted Unathorized
                                      road
               December
                               Naval
                                                                                       0
                                                          no
                 17,2018 academy road
                           Dhaka Ctg
                 january
                                                                  1
                                                                                       0
           36
                                        4
                                                0
                                                          no
                                                                           0
                 14,2018
                                road
                 january
                              Patiya,
                                                                                       0
           37
                     19
                                        1
                                                0
                                                      0
                                                          no
                                                                  1
                                                                           1
                           Chittagong
                 12,2018
                 january Chokoria, Coxs
                                         3
                                                                           0
                                                                                       0
                                                0
                                                      0
                                                          no
                                                                  1
                 27,2018
                               Bazar
               December
                             Agrabad
                                        1
                                                                                       0
                                                0
                                                      0
                                                         no
                                                                  1
                                                                           0
                 15,2018
                          Access road
          5 rows × 23 columns
In [10]: ## first drop the how column cant deal with it and vehical column
          ## when we drop a column in pandas it will return a new data frame
          df = df.drop('How',1)
          df = df.drop('Date',1)
          df = df.drop('Spot',1)
In [11]: ## lets see it again
          df.head()
Out[11]:
                                                                                  Road
              Types
                                                                  Less
                 of Injured Death Insane Addicted Unathorized
                                                                        overall
                                                                                   bad Unconce
                                                             experience
               road
                                                                               condition
                 1
                         0
                               2
                                                          0
                                                                    0.0
                                                                          0.50
                                                                                     0
```

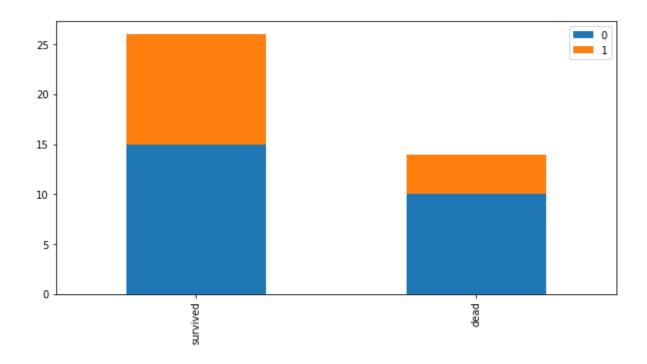
```
Types
                                                                             Road
                                                              Less
                of Injured Death Insane Addicted Unathorized
                                                                   overall
                                                                              bad Unconce
                                                         experience
              road
                                                                          condition
          1
                 2
                       10
                             3
                                    1
                                            0
                                                       0
                                                                0.0
                                                                     0.25
                                                                                0
           2
                 2
                       25
                                            0
                                                       0
                                                                1.0
                                                                     0.50
                                                                                1
           3
                 2
                                    0
                                            0
                       0
                                                       1
                                                               0.0
                                                                     0.25
                                                                                1
                 3
                       2
                             1
                                  1
                                            0
                                                       0
                                                                     0.25
                                                               0.0
                                                                                1
In [12]: list(df.columns.values)
Out[12]: ['Types of road',
           'Injured',
           'Death',
           'Insane',
           'Addicted',
           'Unathorized',
           'Less experience',
           'overall',
           'Road bad condition',
           'Unconcerpedestrian',
           'bad weather',
           'overall.1',
           'Unfitness',
           'no liscence',
           'Aged',
           'overall.2',
           'Unnamed: 19',
           'Average of total fault',
           'Accident',
           'Vehicle']
In [13]: ### unnamed 14 column has mixed thing removing it
          #df=df.drop('Unnamed: 14',1)
In [14]: ##lets see it now
```

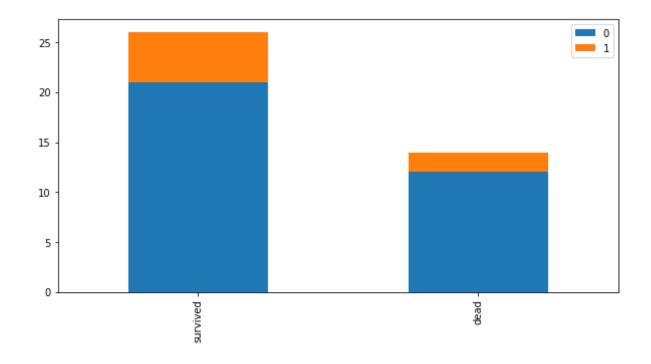
```
df.head()
Out[14]:
             Types
                                                                           Road
                                                            Less
               of Injured Death Insane Addicted Unathorized
                                                                 overall
                                                                            bad Unconce
                                                        experience
                                                                       condition
              road
                       0
                            2
                                                     0
                                                                             0
          0
                1
                                   1
                                           1
                                                              0.0
                                                                   0.50
                                                                             0
          1
                2
                      10
                            3
                                                     0
                                                                   0.25
                                                             0.0
          2
                2
                                   1
                                           0
                                                     0
                      25
                                                             1.0
                                                                   0.50
                                                                             1
          3
                2
                       0
                                   0
                                           0
                                                     1
                                                             0.0
                                                                   0.25
                                                                             1
                3
                       2
                            1
                                           0
                                                     0
                                                             0.0
                                                                   0.25
                                                                             1
In [15]: ## creating a function that can perform relation between the survive an
         d dead people with
         ## other catagory
         ## create a bar chart
         def barchart(feature):
              survived=df[df['Accident']==1][feature].value counts()
              dead=df[df['Accident']==0][feature].value counts()
              #survived1=survived[1]
              #dead1=dead[0]
              df1 = pd.DataFrame([survived,dead])
              dfl.index=['survived','dead']
              df1.plot(kind='bar', stacked=True, figsize=(10,5))
In [16]: ## barchart based on the survived based on different parameter
In [17]: barchart('Addicted') ## how many survived people are addiected and ho
         w many dead are addicted
In [18]: barchart('Insane') # same like this
```



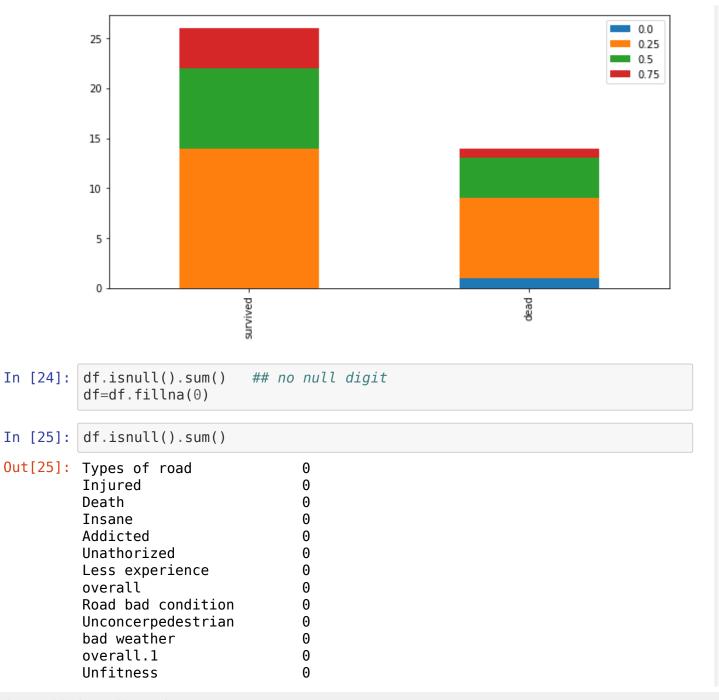


In [20]: barchart('Road bad condition')





In [22]: barchart('overall') ## over all column plotting



```
no liscence
         Aged
         overall.2
         Unnamed: 19
         Average of total fault
         Accident
         Vehicle
         dtype: int64
In [26]: from sklearn.tree import DecisionTreeClassifier
         from sklearn.neighbors import KNeighborsClassifier
         from sklearn.svm import SVC,LinearSVC
         from sklearn.ensemble import RandomForestClassifier,GradientBoostingCla
         ssifier
         ## importing all the algorithm
In [27]: from sklearn.model selection import train test split
         from sklearn.model selection import cross val score
In [28]: x=np.array(df.drop('Accident',1)) ## training featurre
In [29]: y=np.array(df['Accident'])
                                          ## traget values
In [30]: ## slipping the training value
         X train, X test, y train, y test = train test split(x, y, test size=0.3)
In [31]: MachineLearningAlgo=[]
         X=['LinearSVC','DecisionTreeClassifier','KNeighborsClassifier','SVC','G
         radientBoostingClassifier', 'RandomForestClassifier']
         Z=[LinearSVC(),DecisionTreeClassifier(),KNeighborsClassifier(),SVC(),Gr
         adientBoostingClassifier(),RandomForestClassifier()]
In [32]: for model in Z:
             model.fit(X train,y train)
                                           ## training the model this could ta
```

```
ke a little time
              accuracy=model.score(X test,y test) ## comparing result with the
           test data set
             MachineLearningAlgo.append(accuracy) ## saving the accuracy
         /home/vagrant/.local/lib/python3.6/site-packages/sklearn/svm/base.py:19
         6: FutureWarning: The default value of gamma will change from 'auto' to
          'scale' in version 0.22 to account better for unscaled features. Set ga
         mma explicitly to 'auto' or 'scale' to avoid this warning.
           "avoid this warning.", FutureWarning)
         /home/vagrant/.local/lib/python3.6/site-packages/sklearn/ensemble/fores
         t.py:246: FutureWarning: The default value of n estimators will change
         from 10 in version 0.20 to 100 in 0.22.
            "10 in version 0.20 to 100 in 0.22.", FutureWarning)
In [33]: MachineLearningAlgo
Out[33]: [0.916666666666666, 1.0, 0.66666666666666, 0.75, 1.0, 1.0]
In [34]: d={'Accuracy':MachineLearningAlgo,'Algorithm':X}
         df1=pd.DataFrame(d)
In [35]: df1
Out[35]:
                                Algorithm
            Accuracy
          0 0.916667
                               LinearSVC
                        DecisionTreeClassifier
          1 1.000000
          2 0.666667
                         KNeighborsClassifier
          3 0.750000
                                   SVC
          4 1.000000 GradientBoostingClassifier
          5 1.000000
                      RandomForestClassifier
```

this is only happen when we get small data set Linear svc done preety well but we get 100% accuracy its only happen in small data set this is from different classification algorithm not from tensor flow so we can compare the result

using tensorflow and keras for deep nural network

```
In [36]: import tensorflow as tf
In [37]: ## using sequential deep nural network
       model = tf.keras.models.Sequential()
In [38]: ## adding 5 hidden layer
       model.add(tf.keras.layers.Flatten()) #first layer have to be flatten
       model.add(tf.keras.layers.Dense(128,activation = tf.nn.relu)) ## then w
        e added a dense layer
       model.add(tf.keras.layers.Dense(128,activation = tf.nn.relu))
       model.add(tf.keras.layers.Dense(128,activation = tf.nn.relu))
        model.add(tf.keras.layers.Dense(2,activation = tf.nn.softmax))
In [39]: model.compile(optimizer='adam',loss='sparse categorical crossentropy',m
        etrics=['accuracv'])
       we use 1 flatten layer and 5 dense layer that means 6 hidden layer and
       we use 300 iteration for training the DNN model in tensorflow
In [40]: model.fit(X train,y train,epochs=300)
        Epoch 1/300
       acc: 0.3571
        Epoch 2/300
```

```
acc: 0.5714
Epoch 3/300
acc: 0.6786
Epoch 4/300
acc: 0.6429
Epoch 5/300
28/28 [============== ] - 0s 604us/step - loss: 0.4636 -
acc: 0.6429
Epoch 6/300
acc: 0.6429
Epoch 7/300
acc: 0.6429
Epoch 8/300
acc: 0.6429
Epoch 9/300
acc: 0.7143
Epoch 10/300
acc: 0.8571
Epoch 11/300
acc: 0.9643
Epoch 12/300
acc: 1.0000
Epoch 13/300
acc: 1.0000
Epoch 14/300
cc: 1.0000
Epoch 15/300
```

```
acc: 1.0000
Epoch 16/300
acc: 1.0000
Epoch 17/300
acc: 1.0000
Epoch 18/300
acc: 1.0000
Epoch 19/300
28/28 [============== ] - 0s 579us/step - loss: 0.1683 -
acc: 1.0000
Epoch 20/300
28/28 [============== ] - 0s 1ms/step - loss: 0.1512 - a
cc: 1.0000
Epoch 21/300
acc: 1.0000
Epoch 22/300
cc: 1.0000
Epoch 23/300
acc: 1.0000
Epoch 24/300
cc: 1.0000
Epoch 25/300
28/28 [============== ] - 0s 1ms/step - loss: 0.0838 - a
cc: 1.0000
Epoch 26/300
cc: 1.0000
Epoch 27/300
acc: 1.0000
Epoch 28/300
```

```
cc: 1.0000
Epoch 29/300
acc: 1.0000
Epoch 30/300
acc: 1.0000
Epoch 31/300
28/28 [============== ] - 0s 836us/step - loss: 0.0358 -
acc: 1.0000
Epoch 32/300
acc: 1.0000
Epoch 33/300
28/28 [============== ] - 0s 611us/step - loss: 0.0269 -
acc: 1.0000
Epoch 34/300
acc: 1.0000
Epoch 35/300
acc: 1.0000
Epoch 36/300
cc: 1.0000
Epoch 37/300
acc: 1.0000
Epoch 38/300
acc: 1.0000
Epoch 39/300
cc: 1.0000
Epoch 40/300
acc: 1.0000
Epoch 41/300
```

```
acc: 1.0000
Epoch 42/300
cc: 1.0000
Epoch 43/300
28/28 [============== ] - 0s 856us/step - loss: 0.0071 -
acc: 1.0000
Epoch 44/300
cc: 1.0000
Epoch 45/300
28/28 [============== ] - 0s 572us/step - loss: 0.0056 -
acc: 1.0000
Epoch 46/300
28/28 [============== ] - 0s 725us/step - loss: 0.0051 -
acc: 1.0000
Epoch 47/300
cc: 1.0000
Epoch 48/300
acc: 1.0000
Epoch 49/300
acc: 1.0000
Epoch 50/300
acc: 1.0000
Epoch 51/300
28/28 [============= ] - 0s 1ms/step - loss: 0.0031 - a
cc: 1.0000
Epoch 52/300
acc: 1.0000
Epoch 53/300
acc: 1.0000
Epoch 54/300
```

```
acc: 1.0000
Epoch 55/300
acc: 1.0000
Epoch 56/300
cc: 1.0000
Epoch 57/300
cc: 1.0000
Epoch 58/300
acc: 1.0000
Epoch 59/300
cc: 1.0000
Epoch 60/300
acc: 1.0000
Epoch 61/300
acc: 1.0000
Epoch 62/300
acc: 1.0000
Epoch 63/300
cc: 1.0000
Epoch 64/300
28/28 [============== ] - 0s 1ms/step - loss: 0.0012 - a
cc: 1.0000
Epoch 65/300
acc: 1.0000
Epoch 66/300
acc: 1.0000
Epoch 67/300
```

```
04 - acc: 1.0000
Epoch 68/300
28/28 [============== ] - 0s 541us/step - loss: 9.4618e-
04 - acc: 1.0000
Epoch 69/300
28/28 [============== ] - 0s 1ms/step - loss: 8.9740e-04
- acc: 1.0000
Epoch 70/300
- acc: 1.0000
Epoch 71/300
04 - acc: 1.0000
Epoch 72/300
28/28 [============== ] - 0s 814us/step - loss: 7.7024e-
04 - acc: 1.0000
Epoch 73/300
04 - acc: 1.0000
Epoch 74/300
- acc: 1.0000
Epoch 75/300
04 - acc: 1.0000
Epoch 76/300
28/28 [============= ] - 0s 1ms/step - loss: 6.2585e-04
- acc: 1.0000
Epoch 77/300
04 - acc: 1.0000
Epoch 78/300
04 - acc: 1.0000
Epoch 79/300
- acc: 1.0000
Epoch 80/300
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04 - acc: 1.0000
Epoch 81/300
- acc: 1.0000
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Epoch 87/300
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Epoch 88/300
- acc: 1.0000
Epoch 89/300
04 - acc: 1.0000
Epoch 90/300
28/28 [============= ] - 0s 1ms/step - loss: 3.3755e-04
- acc: 1.0000
Epoch 91/300
04 - acc: 1.0000
Epoch 92/300
04 - acc: 1.0000
Epoch 93/300
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- acc: 1.0000
Epoch 94/300
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Epoch 95/300
04 - acc: 1.0000
Epoch 96/300
- acc: 1.0000
Epoch 97/300
04 - acc: 1.0000
Epoch 98/300
28/28 [============== ] - 0s 1ms/step - loss: 2.4428e-04
- acc: 1.0000
Epoch 99/300
04 - acc: 1.0000
Epoch 100/300
04 - acc: 1.0000
Epoch 101/300
- acc: 1.0000
Epoch 102/300
28/28 [============= ] - 0s 1ms/step - loss: 2.0745e-04
- acc: 1.0000
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Epoch 142/300
28/28 [============= ] - 0s 1ms/step - loss: 4.5449e-05
- acc: 1.0000
Epoch 143/300
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Epoch 145/300
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Epoch 186/300
28/28 [============= ] - Os 672us/step - loss: 1.4641e-
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Epoch 259/300
06 - acc: 1.0000
Epoch 260/300
- acc: 1.0000
Epoch 261/300
06 - acc: 1.0000
Epoch 262/300
```

```
06 - acc: 1.0000
Epoch 263/300
06 - acc: 1.0000
Epoch 264/300
06 - acc: 1.0000
Epoch 265/300
- acc: 1.0000
Epoch 266/300
06 - acc: 1.0000
Epoch 267/300
06 - acc: 1.0000
Epoch 268/300
06 - acc: 1.0000
Epoch 269/300
06 - acc: 1.0000
Epoch 270/300
06 - acc: 1.0000
Epoch 271/300
06 - acc: 1.0000
Epoch 272/300
06 - acc: 1.0000
Epoch 273/300
06 - acc: 1.0000
Epoch 274/300
06 - acc: 1.0000
Epoch 275/300
```

```
06 - acc: 1.0000
Epoch 276/300
06 - acc: 1.0000
Epoch 277/300
28/28 [============= ] - Os 308us/step - loss: 4.6661e-
06 - acc: 1.0000
Epoch 278/300
06 - acc: 1.0000
Epoch 279/300
06 - acc: 1.0000
Epoch 280/300
06 - acc: 1.0000
Epoch 281/300
- acc: 1.0000
Epoch 282/300
06 - acc: 1.0000
Epoch 283/300
06 - acc: 1.0000
Epoch 284/300
06 - acc: 1.0000
Epoch 285/300
06 - acc: 1.0000
Epoch 286/300
06 - acc: 1.0000
Epoch 287/300
06 - acc: 1.0000
Epoch 288/300
```

```
06 - acc: 1.0000
   Epoch 289/300
   06 - acc: 1.0000
   Epoch 290/300
   28/28 [============= ] - 0s 756us/step - loss: 4.1638e-
   06 - acc: 1.0000
   Epoch 291/300
   06 - acc: 1.0000
   Epoch 292/300
   - acc: 1.0000
   Epoch 293/300
   06 - acc: 1.0000
   Epoch 294/300
   - acc: 1.0000
   Epoch 295/300
   06 - acc: 1.0000
   Epoch 296/300
   06 - acc: 1.0000
   Epoch 297/300
   06 - acc: 1.0000
   Epoch 298/300
   06 - acc: 1.0000
   Epoch 299/300
   06 - acc: 1.0000
   Epoch 300/300
   06 - acc: 1.0000
Out[40]: <tensorflow.python.keras.callbacks.History at 0x7fa285ce8518>
```

Final result comparison

```
In [44]: df2
Out[44]:
                                        Algorithm
                Accuracy
               0.916667
                                        LinearSVC
                1.000000
                              DecisionTreeClassifier
                0.666667
                               KNeighborsClassifier
             3
                0.750000
                                             SVC
               1.000000 GradientBoostingClassifier
                             RandomForestClassifier
                1.000000
                0.750000
                                 Deep nural network
```

In []: