

# Assignment 7

## Prostate Cancer Identification

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# Initial Handling of Training And Test Data

We started with combining data to make sure any adjustments in training will be applied to test data as well.

The result was 26916 instances and 33 variables.

Initially, we were hesitant to change the variables as it was mentioned in the assignment not to change.

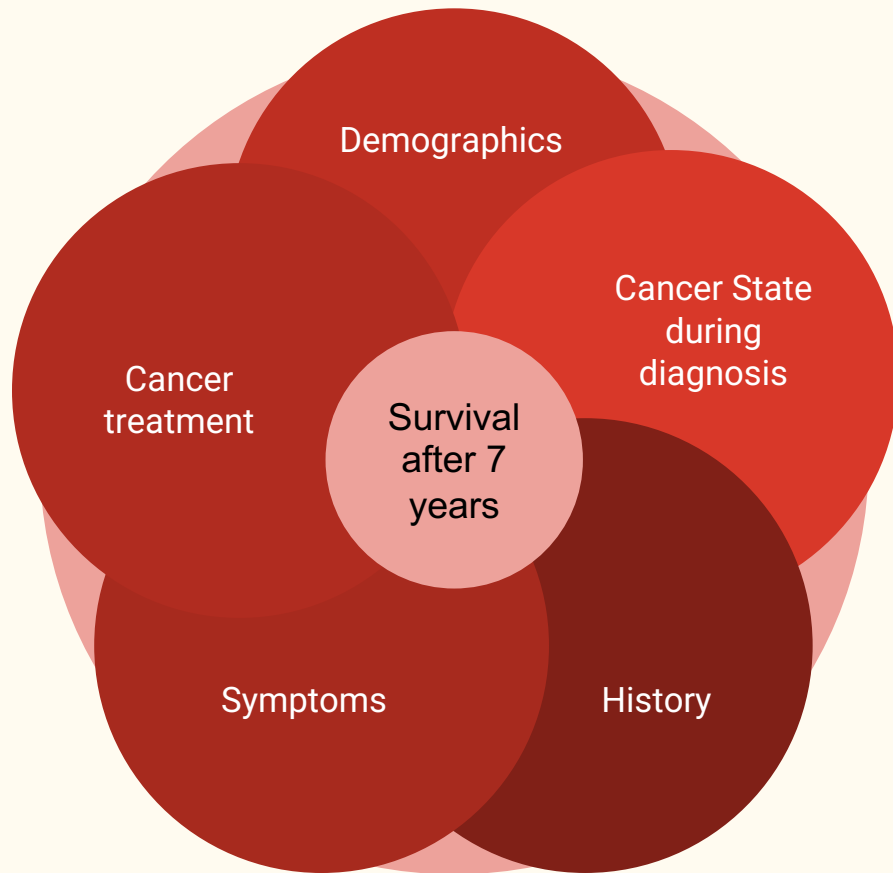
```
▶ df1 = pd.concat([df, dfscore])
```

```
[ ] len(df1)
```

```
26916
```

# Feature Selection

1. Demographics:
  - Age
  - Race
  - Obesity
1. Cancer treatment
  - Kind of Therapy
  - Surgery
1. Symptoms
  - All Symptoms
1. History
  - Family history
  - Smoker
  - Previous Cancer diagnosis
1. Cancer State during diagnosis
  - Stage
  - Tumor size
  - Gleason score
  - T\_score, n\_score, m\_score
  - side



# EDA - Univariate Analysis

- Checking for null-values in both training and test data
- We can see most of the columns with null values are common in Train and test data.
- We can see that survival\_1\_year flag has a lot of null values in test data. We chose to exclude it from our data.
- In addition, we created new binary feature called Obesity based on Height (inches) and Weight (lbs). (BMI > 30 - 1 else 0)

	data_null	test_null
id	0	0
diagnosis_date	0	0
gleason_score	320	239
t_score	0	0
n_score	0	0
m_score	0	0
stage	0	0
age	748	648
race	165	121
height	1364	1043
weight	1317	1041
BMI	2567	1987
Obesity	2567	1987
family_history	1586	1171
first_degree_history	1586	1171
previous_cancer	1586	1171
smoker	1586	1171
side	0	0
tumor_diagnosis	303	210
rd_thrpy	0	0
h_thrpy	0	0
chm_thrpy	0	0
cry_thrpy	0	0
brch_thrpy	0	0
rad_rem	0	0
multi_thrpy	0	0
survival_1_year	0	5713
O01	0	0
O08	0	0
O09	0	0
O10	0	0
O11	0	0
P01	0	0
P02	0	0
P03	0	0
S04	0	0
S07	0	0
S10	0	0
U01	0	0
U02	0	0
U03	0	0
U05	0	0
U06	0	0
survival_7_years	0	11531

# Univariate Analysis

- We divided the data by classes of target variable
- Checking the null values in both classes, We see similar distribution of nulls among variables across both classes
- Therefore, we might have to classify null values as a separate category which can be used in predicting test data.

	Class1_null	Class0_null
diagnosis_date	0	0
gleason_score	147	173
t_score	0	0
n_score	0	0
m_score	0	0
stage	0	0
age	314	434
race	73	92
Obesity	1070	1497
family_history	700	886
first_degree_history	700	886
previous_cancer	700	886
smoker	700	886
side	0	0
tumor_diagnosis	127	176
rd_thrpy	0	0
h_thrpy	0	0
chm_thrpy	0	0
cry_thrpy	0	0
brch_thrpy	0	0
rad_rem	0	0
multi_thrpy	0	0
survival_1_year	0	0
O01	0	0
O08	0	0
O09	0	0
O10	0	0
O11	0	0
P01	0	0
P02	0	0
P03	0	0
S04	0	0
S07	0	0
S10	0	0
U01	0	0
U02	0	0
U03	0	0
U05	0	0
U06	0	0
survival_7_years	0	0

# Feature engineering - Symptoms

Create features for each type of symptoms:

- Splitting the symptoms column by the delimiter ‘,’
- There are a maximum of 9 symptoms for a patient
- Finding the unique symptoms present
- Now create new symptom features for all the 16 symptoms.

A	B	C	D	E	F	G	H	I	Sym Code
symptom1	symptom2	symptom3	symptom4	symptom5	symptom6	symptom7	symptom8	symptom9	
0	0	0	0	0	0	0	0	0	O01
O01	O01	O01	O01	O01	O01	O01	O01	O10	O08
O08	O08	O08	O08	O08	O08	O08	O08	O11	O09
O09	O09	O09	O09	O09	O09	O09	O09		O10
O10	O10	O10	O10	O10	O10	O10	O10		O11
O11	O11	O11	O11	O11	O11	O11	O11		
P01	P01	P01	P01	P01	P01	P01	S10		P01
P02	P02	P02	P02	P02	P02	P02			P02
P03	P03	P03	P03	P03	P03	S04			P03
S04	S04	S04	S04	S04	S04	S10			S04
S07	S07	S07	S07	S07	S07				S07
S10	S10	S10	S10	S10	S10				S10
U01				U06					U01
U02	U02								U02
U03	U03	U03							U03
U05	U05	U05	U05						U05
U06	U06	U06	U06						U06

# Feature Engineering - Age and Gleason score

- We categorised the age into categories:
  1. Age\_group = 1 if age  $\leq$  45
  2. Age\_group = 2 if  $45 < \text{age} < 60$
  3. Age\_group = 3 if  $60 \leq \text{age} < 75$
  4. Age\_group = 4 if age  $\geq$  75
- We categorised Gleason score into gleason grades:
  1. Gleason grade = 1 if gleason score  $< 7$
  2. Gleason grade = 2 if  $7 \leq \text{gleason score} < 8$
  3. Gleason grade = 3 if  $8 \leq \text{gleason score} < 9$
  4. Gleason grade = 4 if gleason score  $\geq 9$

```
def replace_age(val):  
    if val <= 45:  
        return 1  
    elif val > 45 and val < 60:  
        return 2  
    elif val >= 60 and val < 75:  
        return 3  
    elif val >= 75:  
        return 4  
    else:  
        return val
```

```
def replace_gleason_score(val):  
    if val < 7:  
        return 1  
    elif val >= 7 and val < 8:  
        return 2  
    elif val >= 8 and val < 9:  
        return 3  
    elif val >= 9:  
        return 4  
    else:  
        return val
```

# Feature Engineering - Family history and First degree

- Reduced the categories in family history to 5 (0,1,2,3,NA)
- Reduced the categories in First degree history to 4 (0,1,2,3,NA)

```
def replace_first_degree_history(val):  
    if val > 2:  
        return 2  
    else:  
        return val  
  
df_c['first_degree_history'] = df_c['first_degree_history'].apply(replace_first_degree_history)
```

```
def replace_family_history(val):  
    if val > 3:  
        return 3  
    else:  
        return val  
  
df_c['family_history'] = df_c['family_history'].apply(replace_family_history)
```



# Feature engineering - stage

Change stage to numbers. Here we changed to IIA and IIB to 2 only as it is one of the four stages of prostate cancer.

```
19 df6.loc[(df6['stage'] == 'I'), 'stage'] = '1'
20 df6.loc[(df6['stage'] == 'IIA'), 'stage'] = '2'
21 df6.loc[(df6['stage'] == 'IIB'), 'stage'] = '2'
22 df6.loc[(df6['stage'] == 'III'), 'stage'] = '3'
23 df6.loc[(df6['stage'] == 'IV'), 'stage'] = '4'
24 |
25
26 df6.head()
```

	stage	side	rd_thrpy	h_thrpy	chm_thrpy	cry_thrpy	brch_thrpy	rad_rem	multi_thrpy	symptoms	survival_7_years
0	1	both	0	0	1	1	0	1	1	U03	0.0
1	4	both	1	1	1	0	0	0	1	U06,S07	0.0
2	2	right	1	1	0	0	1	1	1	U01,U02,U03,S10	1.0
3	2	right	0	0	0	1	0	1	1	U01,U02,S10,O11	0.0
4	4	left	1	1	1	0	0	0	1	U01,U03,U05,S07	0.0

# Final features

- For building the model, we used 24 features listed below:

```
df_f.columns
```

```
Index(['stage', 'race', 'Obesity', 'first_degree_history', 'smoker',  
      'tumor_diagnosis', 'rd_thrpy', 'h_thrpy', 'chm_thrpy', 'cry_thrpy',  
      'brch_thrpy', 'rad_rem', 'multi_thrpy', 'O01', 'O08', 'O09', 'O10',  
      'P01', 'P02', 'P03', 'S10', 'U05', 'survival_7_years', 'age_group',  
      'gleason_grade'],  
      dtype='object')
```

# Bivariate Analysis - T-test

- Applied T-test on tumor\_diagnosis variable and target.
- The p\_value of the test is smaller than 0.05
- The tumor\_diagnosis is significant for predicting target variable.

```
print(t_stat)  
print(p_value)
```

```
11.771977006055414  
7.503669578708669e-32
```

# Chi-squared & P value

- Performed Chi-Squared test between categorical variables and target variable.
- Dropping the the symptoms which are insignificant
- Dropping Family history as it turned out to be insignificant and similar information is present in first degree history
- Dropping t\_score, m\_score and n\_score as stage would have similar information.
- Dropping side as it is insignificant
- Keeping smoker in as it might affect target
- Dropping gleason score as we have categorised it into gleason grades
- Replaced all the null values with '-1', i.e. classifying as a separate class.

	Column	Chi-Squared	P-Value	Degrees of Freedom
0	gleason_score	441.973316	1.076126e-88	10
1	t_score	169.063670	9.668435e-32	9
2	n_score	869.336301	1.682755e-189	2
3	m_score	379.792151	5.272716e-82	3
4	stage	698.852773	6.175118e-150	4
5	race	14.741022	2.051886e-03	3
6	Obesity	12.939614	3.217013e-04	1
7	family_history	3.686167	2.974074e-01	3
8	first_degree_history	9.306678	9.529728e-03	2
9	previous_cancer	5.577015	1.819771e-02	1
10	smoker	0.766161	3.814072e-01	1
11	side	0.768288	6.810332e-01	2
12	rd_thrpy	267.649264	3.691901e-60	1
13	h_thrpy	4.981030	2.562672e-02	1
14	chm_thrpy	114.008319	1.297630e-26	1
15	cry_thrpy	48.137145	3.974260e-12	1
16	brch_thrpy	37.438869	9.432350e-10	1
17	rad_rem	4.472554	3.444347e-02	1
18	multi_thrpy	75.772995	3.182235e-18	1
19	001	103.023938	3.311231e-24	1
20	008	97.245800	6.123375e-23	1
21	009	94.595514	2.335470e-22	1
22	010	40.043632	2.483531e-10	1
23	011	0.194753	6.589898e-01	1
24	P01	169.018014	1.212399e-38	1
25	P02	124.825685	5.556777e-29	1
26	P03	57.435510	3.492447e-14	1
27	S04	1.045269	3.065991e-01	1
28	S07	3.548126	5.961273e-02	1
29	S10	75.678960	3.337449e-18	1
30	U01	1.009527	3.150162e-01	1
31	U02	0.391786	5.313623e-01	1
32	U03	0.069136	7.925984e-01	1
33	U05	65.344377	6.288910e-16	1
34	U06	0.321680	5.705999e-01	1
35	age_group	9.328606	2.522638e-02	3
36	gleason_grade	404.418195	2.444162e-87	3

# Models and Accuracy

- Built a Support Vector Machine model on the train data and predicted on validation data
- Accuracy on validation data is 63.15%

```
[ ] svm_model = SVC(kernel='linear')  
svm_model.fit(X_train, y_train)
```

▼ SVC  
SVC(kernel='linear')

```
[ ] y_pred = svm_model.predict(X_test)  
accuracy = accuracy_score(y_test, y_pred)  
print(f"Accuracy: {accuracy}")
```

Accuracy: 0.6314991334488734

## Alternate models:

We used Random forest classifier and Decision classifier we received less accuracy compared to SVM

```
rf = RandomForestClassifier(n_estimators=300, random_state=2)
rf.fit(X_train, y_train)
y_pred = rf.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)
```

Accuracy: 0.5870883882149047

```
dt = DecisionTreeClassifier(random_state=42)
dt.fit(X_train, y_train)
y_pred = dt.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)
```

Accuracy: 0.5576256499133448

# Test Data Prediction

- Finally, we used the SVM to predict on test data.
- Generated a csv file with the predictions and concatenated with score.csv
- On the test data:

survival_7_years	count
1	7418
0	4113

Thank you

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