## Genetic Variant Classifications

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#### Genetic variants come from the changes of DNA sequences

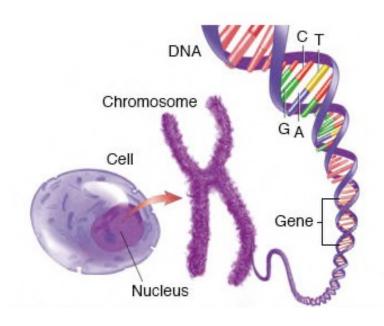


Figure 1: Classes of human genetic variants.

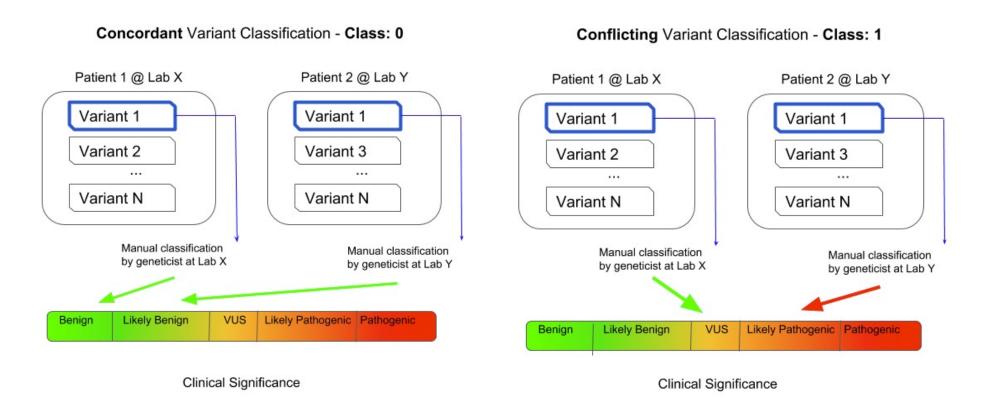
Single nucleotide variant

Insertion-deletion variant

ATTGGCCTTAACCTCCGATTATCAGGAT

ATTGGCCTTAACCCGATCCGATTATCAGGAT
ATTGGCCTTAACCCGATTATCAGGAT

## Genetic variants are classified manually which resulting in conflicting classification



## Data exploration analysis

clinvar\_conflicting.var (Kaggle) (46 features)

#### Remove features

- 1. Redundant
- 2. Not correlated

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 65188 entries, 0 to 65187

Data columns (total 9 columns):

#	Column	Non-Null Count	Dtype
0	CHROM	65188 non-null	object
1	CLNVC	65188 non-null	object
2	MC	64342 non-null	object
3	IMPACT	65188 non-null	object
4	SYMBOL	65172 non-null	object
5	AF_ESP	65188 non-null	float64
6	LoFtool	60975 non-null	float64
7	CADD_PHRED	64096 non-null	float64
8	CLASS	65188 non-null	int64
-			

dtypes: float64(3), int64(1), object(5)

memory usage: 4.5+ MB

**CLNVC - Variant Type** 

MC - Molecular consequence

IMPACT - the impact of the variants

SYMBOL - Gene Name

AF\_ESP - Allele frequencies

LoFtool - Loss of Function tolerance score

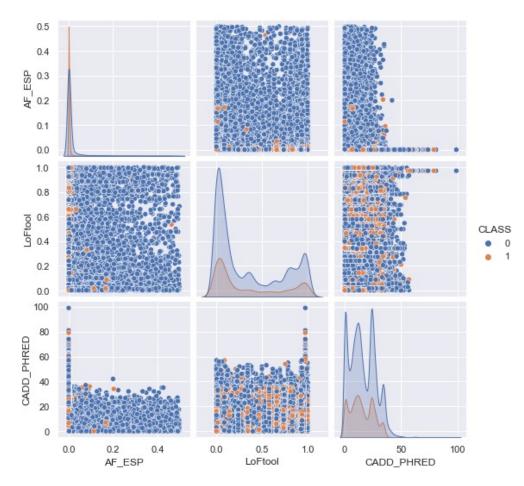
CADD\_PHRED - Scoring the deleteriousness of the variants

# AF\_ESP and SYMBOL are more distinguishable among 2 classes

Chi2 test for categorical features (p-value)

	CLASS
снком	1.407244e-05
CLASS	NaN
IMPACT	1.856664e-191
SYMBOL	6.362397e-309

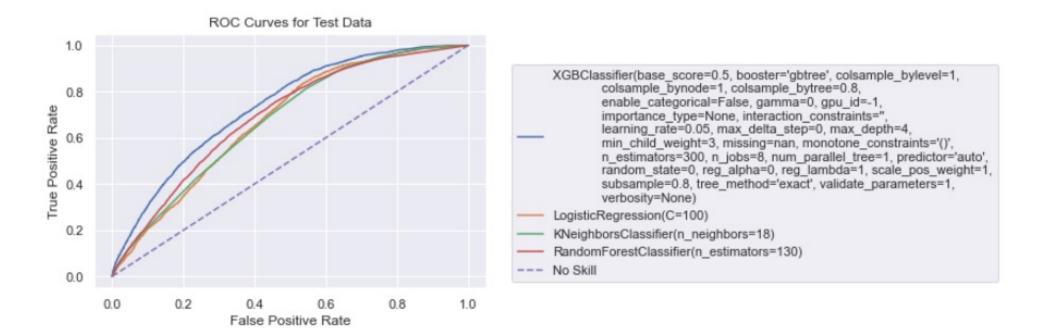
#### Pairplot for numerical features

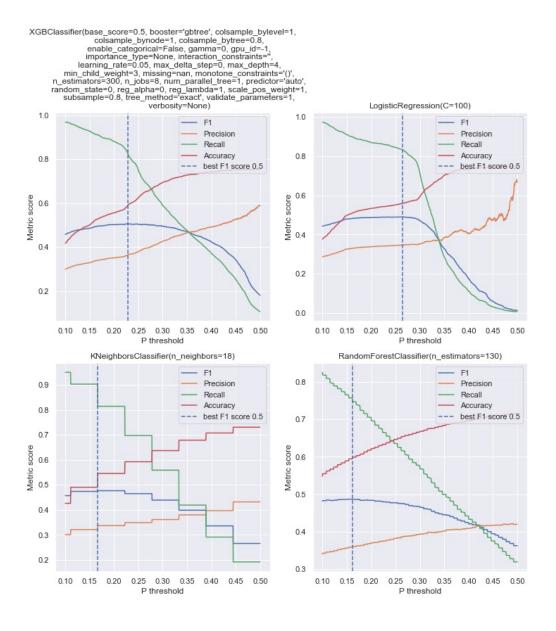


## Data preprocessing

- Convert categorical feature into dummies variables
- Scale the numerical data
- Class rebalance
- Model fitting

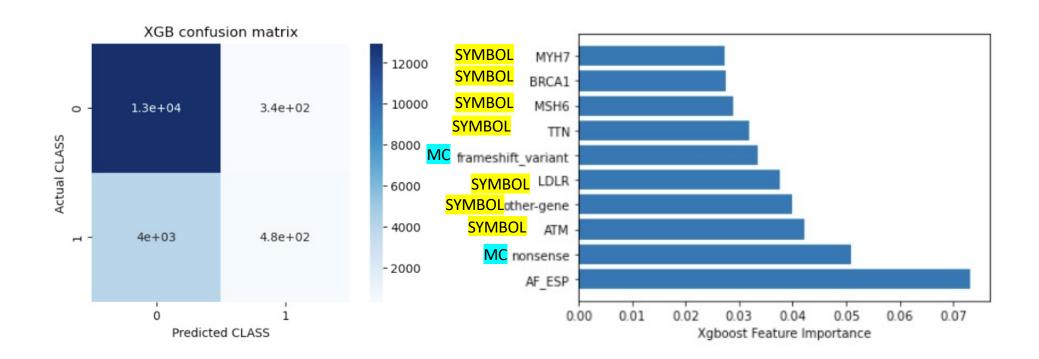
### XGBoost tree has better performance for the prediction





# All 4 models have similar F1 scores

# AF (variant frequency), symbol (gene names) and MC(molecular consequences) are the important features



## Questions