

Twitter User Gender Classification using SparkML

Project Report

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Data Processing Steps

List of Data Issues found in raw data

1. New lines, Non Ascii characters in text data
2. Few malformed CSV lines
3. "Unknown" gender value
4. Gender judgement by reviewers with lower confidence
5. Text with multiple words, common stop words

How did you tackle the issues mentioned above?

1. Used `option("mode", "DROPMALFORMED")` while loading csv data to clear malformed and problematic records
2. Filtered records with predicted gender value & good confidence for better accuracy (~61% records net obtained)
3. **RegexTokenizer** to tokenize the words, **explode** inbuilt udf to split words into multiple rows and **StopWordsRemover** to remove common words

```
Dataset<Row> reduced = userKnowDf.select(
    col("_golden"),
    col("gender"),
    col("gender:confidence"),
    col("gender_gold"),
    col("description"),
    col("sidebar_color"),//.cast("long"),
    col("link_color"),//.cast("long"),
    col("text"),
    col("tweet_location"),
    col("user_timezone")
)
.filter("`gender:confidence` == 1") //filter low
//gender confidence records for better model accuracy
.filter("gender == 'male' or gender == 'female' or gender == 'brand'"); //eliminate
//unreliable data
```

```
RegexTokenizer tokenizer = new RegexTokenizer()
.setInputCol("text")
.setOutputCol("words")
.setPattern("\\W");

//remove commonly used words
StopWordsRemover remover = new StopWordsRemover()
.setInputCol("words")
.setOutputCol("filtered_words");
```

```
Dataset<Row> word_result = filtered.sqlContext()
    .sql("SELECT _golden, gender,`gender:confidence`,gender_gold"
        + ",sidebar_color,link_color,tweet_location,user_timezone, word "
        + "FROM parent LATERAL VIEW explode(filtered_words) childTable AS word");
```

Input Records

unit_id	golden	unit_state	trusted_jud	last_judgm	gender	gender:confi	text
815719226	FALSE	finalized		3 10/26/15 23:2	male		1 Robbie E Responds To Critics After Win Against Eddie Edwards In The #WorldTitleSe
815719227	FALSE	finalized		3 10/26/15 23:3	male		1 ♠♠♠It felt like they were my friends and I was living the story with them♠ https:
815719228	FALSE	finalized		3 10/26/15 23:3	male	0.6625	1 absolutely adore when louis starts the songs it hits me hard but it feels good
815719229	FALSE	finalized		3 10/26/15 23:1	male		1 Hi @JordanSpieth - Looking at the url - do you use @IFTTT?! Don't typically see an
815719245	FALSE	finalized		3 10/26/15 22:1	unknown	0.3527	

Output

_golden	gender	gender:confidence	gender_gold	sidebar_color	link_color	tweet_location	user_timezone	word
FALSE	male	1	null	FFFFFF	08C2C2	main; @Kan1shk3	Chennai	robbie
FALSE	male	1	null	FFFFFF	08C2C2	main; @Kan1shk3	Chennai	e
FALSE	male	1	null	FFFFFF	08C2C2	main; @Kan1shk3	Chennai	responds
FALSE	male	1	null	FFFFFF	08C2C2	main; @Kan1shk3	Chennai	critics
FALSE	male	1	null	FFFFFF	08C2C2	main; @Kan1shk3	Chennai	win
FALSE	male	1	null	FFFFFF	08C2C2	main; @Kan1shk3	Chennai	eddie
FALSE	male	1	null	FFFFFF	08C2C2	main; @Kan1shk3	Chennai	edwards
FALSE	male	1	null	FFFFFF	08C2C2	main; @Kan1shk3	Chennai	worldtitleseries
FALSE	male	1	null	FFFFFF	08C2C2	main; @Kan1shk3	Chennai	https
FALSE	male	1	null	FFFFFF	08C2C2	main; @Kan1shk3	Chennai	co
FALSE	male	1	null	FFFFFF	08C2C2	main; @Kan1shk3	Chennai	nsybbmvjkz
FALSE	male	1	null	C0DEED	0084B4	null	Eastern Time (US ...	felt
FALSE	male	1	null	C0DEED	0084B4	null	Eastern Time (US ...	like
FALSE	male	1	null	C0DEED	0084B4	null	Eastern Time (US ...	friends
FALSE	male	1	null	C0DEED	0084B4	null	Eastern Time (US ...	living
FALSE	male	1	null	C0DEED	0084B4	null	Eastern Time (US ...	story
FALSE	male	1	null	C0DEED	0084B4	null	Eastern Time (US ...	https
FALSE	male	1	null	C0DEED	0084B4	null	Eastern Time (US ...	co
FALSE	male	1	null	C0DEED	0084B4	null	Eastern Time (US ...	arnge0yhno
FALSE	male	1	null	C0DEED	0084B4	null	Eastern Time (US ...	retired

Model Building

List of Models used

1. Decision Tree Algorithm
 - I. Columns
 - a) Label
 - i. gender
 - b) Features
 - i. text
 - ii. sidebar_color (4-5% improved accuracy)
 - iii. link_color (4-5% improved accuracy)
 - II. HyperParameters
 - a) maxDepth – 20 (Test Data Accuracy = 52%, Training Data Accuracy = 52%)
 - i. Increasing further to 25 caused model to *overfit* (test=53%,train=54%)
 - ii. Lowering to 15 caused to *underfit* (test=50%,train=50%)

```

DecisionTreeClassifier dt = new DecisionTreeClassifier().setLabelCol("label").setFeaturesCol("features").setSeed(0);
dt.setMaxDepth(20);
dt.setMinInfoGain(0.0);
dt.setMinInstancesPerNode(1);
dt.setCacheNodeIds(false);
dt.setMaxBins(3000);

DecisionTreeClassificationModel Model = dt.fit(trainingData);
System.out.println("Learned Decision tree" + Model.toDebugString());

Dataset<Row> rawPredictions = Model.transform(testData);
Dataset<Row> predictions = predConverter.transform(labelConverter.transform(rawPredictions));
predictions.select("predictionStr", "labelStr", "features").show(5);
/**Test data predictions**/
Dataset<Row> trainRawPredictions = Model.transform(trainingData);
Dataset<Row> trainPredictions = predConverter.transform(labelConverter.transform(trainRawPredictions));
trainPredictions.select("predictionStr", "labelStr", "features").show(5);

```

2. Random Forest Algorithm

I. Columns

- a) Label
 - i. gender
- b) Features
 - i. text
 - ii. sidebar_color (4-5% improved accuracy)
 - iii. link_color (4-5% improved accuracy)

II. HyperParameters

- a) maxDepth – 25 (Accuracy = 55%) (Test Data Accuracy = 52%, Training Data Accuracy = 52%)
 - i. Increasing further to 30 caused no improvement (test=55%,train=55%)
 - ii. No overfitting observed in this model
 - iii. Lowering to 20 caused to *underfit* (test=54%,train=54%)
- b) Increasing minInfoGain to 1.0, minInstancePerNode=5 and setCacheNodeIds=false reduced accuracy to 37%

```

/*******Random Forest*****//
RandomForestClassifier rf = new RandomForestClassifier();
rf.setLabelCol("label").setFeaturesCol("features").setSeed(0);
rf.setMaxDepth(25);
rf.setMinInfoGain(0.0);
rf.setMinInstancesPerNode(1);
rf.setCacheNodeIds(false);
rf.setMaxBins(3000);

RandomForestClassificationModel rfModel = rf.fit(trainingData);
System.out.println("Learned Random Forest Decision tree" + rfModel.toDebugString());
Dataset<Row> rfRawPredictions = rfModel.transform(testData);
Dataset<Row> rfPredictions = predConverter.transform(labelConverter.transform(rfRawPredictions));
rfPredictions.select("predictionStr", "labelStr", "features").show(5);

/**Test data predictions**/
Dataset<Row> rfTrainRawPredictions = rfModel.transform(trainingData);
Dataset<Row> rfTrainPredictions = predConverter.transform(labelConverter.transform(rfTrainRawPredictions));
rfTrainPredictions.select("predictionStr", "labelStr", "features").show(5);

```

Evaluation Metrics

Model	Evaluation Scores				Confusion Matrix
	Accuracy	Precision	Recall	F1	
Decision Tree	52%	Female:0.69 Male:0.41 Brand:0.63 Weighted:0.57	Female:0.48 Male:0.73 Brand:0.33 Weighted:0.51	Female:0.57 Male:0.53 Brand:0.44 Weighted:0.51	+-----+-----+-----+ labelStr predictionStr count +-----+-----+-----+ male brand 1259 male female 2070 female female 6773 male male 9050 brand brand 4007 female male 6216 brand male 6522 female brand 1038 brand female 1428 +-----+-----+-----+
Random Forest	55%	Female:0.71 Male:0.43 Brand:0.69 Weighted:0.61	Female:0.49 Male:0.77 Brand:0.36 Weighted:0.55	Female:0.58 Male:0.55 Brand:0.47 Weighted:0.54	+-----+-----+-----+ labelStr predictionStr count +-----+-----+-----+ male brand 1086 male female 1668 female female 6996 male male 9625 brand brand 4316 female male 6221 brand male 6488 female brand 810 brand female 1153 +-----+-----+-----+

Model Fit

Model	Max Depth	Test Data Accuracy %	Training Data Accuracy %	Fit
Decision Tree	10	47	47	Under
Decision Tree	15	50	50	Under
Decision Tree	20	52	52	Right
Decision Tree	25	53	54	Over
Random Forest	10	49	49	Under
Random Forest	15	52	52	Under
Random Forest	20	54	54	Under
Random Forest	25	55	55	Right
Random Forest	30	55	55	No Change

Inferences and suggestions

1. Results Comparision

Model	Pros	Cons
Decision Tree	Fast Execution	Low Accuracy Prone to overfitment
Random Tree	Better Accuracy Less prove to overfitment	Slower compared to Decision Tree

Random Forest and clearly better algorithm than decision tree in terms of its prediction accuracy & overfitting issue. MaxDepth – Increasing max depth improved accuracy until a point after which it lead to overfitting. Random forest was less affected by overfitment than decision tree. In given data, there was no further improvement due to other hyperparameters:

-

HyperParameter	Value	Algorithm	New Accuracy
minInfoGain	0 to 1	Decision Tree	37% (Reduced)
minInstancesPerNode	0 to 3	Decision Tree	52% (No change)
minInfoGain	0 to 1	Random Forest	55% (No change)
minInstancesPerNode	0 to 3	Random Forest	55% (No change)

2. Improvisation techniques

1. Tuning more hyperparameters: -

1. **MinInfoGain** – Increasing this parameter can improve stopping criteria there by increasing speed of anlaysis
2. **MinInstancesPerNode** – By increasing minimum number of required split candidates in order to consider it for training, it can improve accuracy in case of deeper training algorithm like random forest

2. Trying other type of classification algorithms like Naive Bayes, Boosted Trees, Neural Networks etc.

3. Choice of preferred Algorithm

Random Forest is preffered choice of algorithm among the two due to better accuracy & better fitment with same training data.