The General: NLP Predictions

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4 Predictions Based on Text

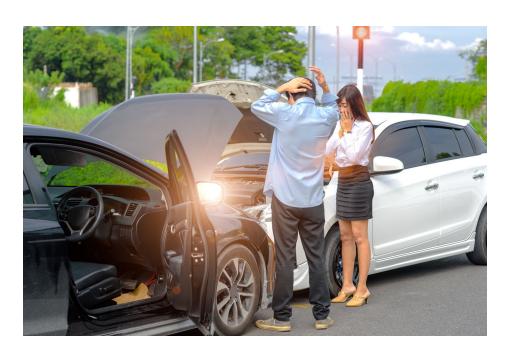
- 1. Who's at fault?
- 2. What claim group should it be routed to?
- 3. What is the severity type?
- 4. What is the loss cause?

Can you predict who is a fault for an accident?

Who is at fault?

- Insured at fault
 - IV rear ended CV
- Other party at fault
 - CV rear ended IV
- Comparative negligence
 - o iv ran a red light causing iv to strike cv causing cv to strike a pole
- No fault
 - IV struck a deer
- Fault unknown
 - iv was making a left turn at an intersection and iv struck a pedestrian iv states he crossed the road behind a truck and the pedestrian walked into iv

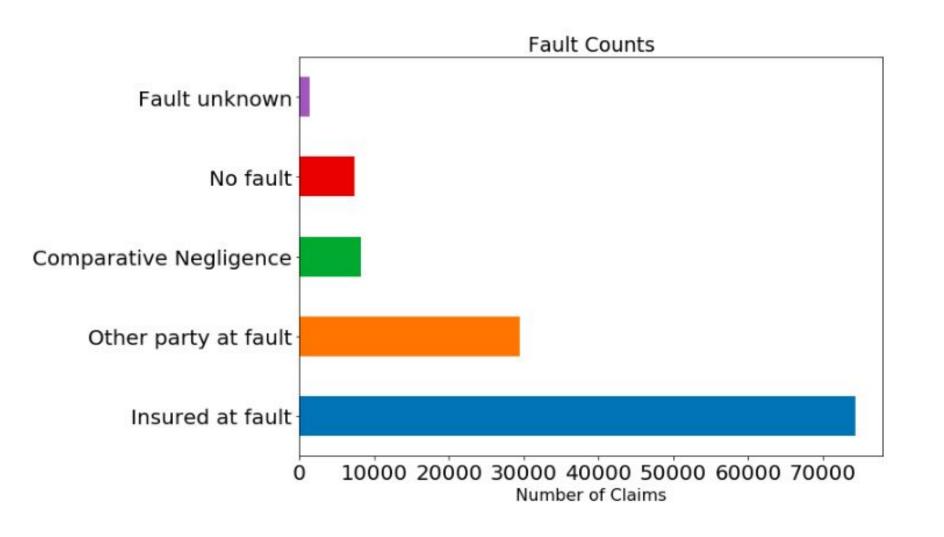
Why does it matter who's at fault?

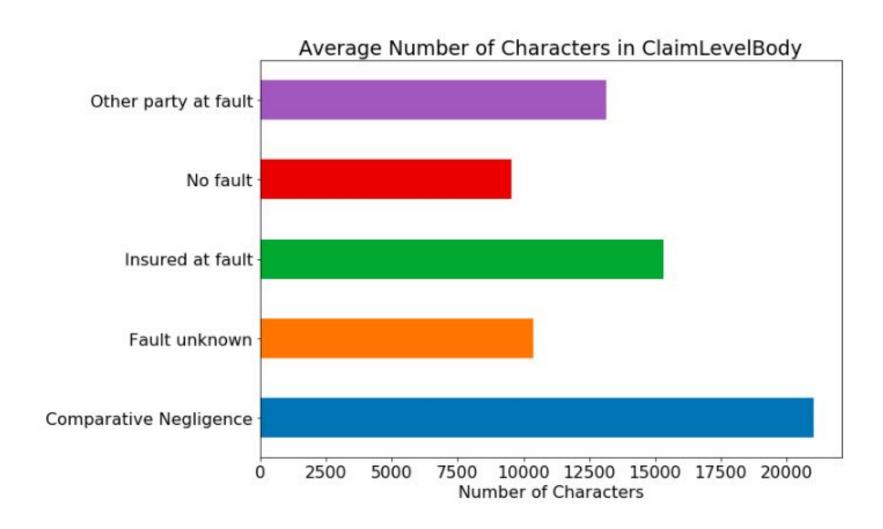


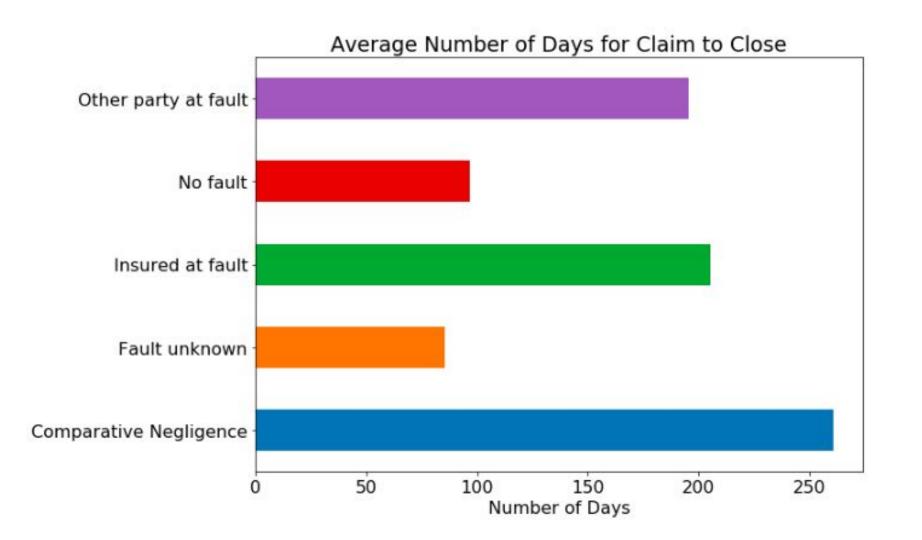
Step 1: Cleaning / Pre-Processing

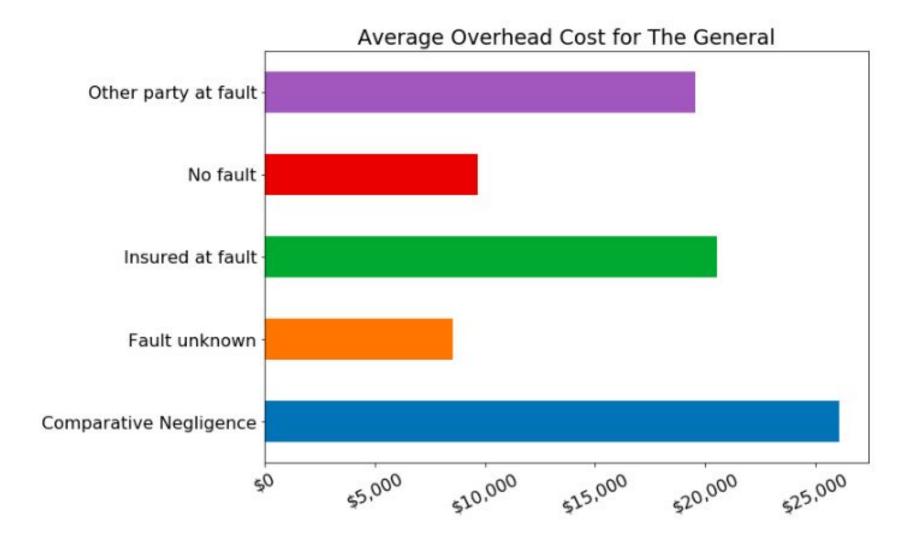
- Claim-level question → Drop multiple exposures to avoid overfitting
 - Done on CCCreateTime since it's unique
- Fix characters
 - k 0
 - 0 \r
 - \n
 - o re
- Remove stop words and punctuations
- Convert to lowercase

Step 2: EDA









Step 3: Machine Learning

- Which column of text to use as features?
 - ClaimLevelBody vs. Accident Description vs. Damage Description
- Which vectorizer to use?
 - CountVectorizer vs. TF-IDF
- Which classifier?
 - Naive Bayes vs. SGD

```
vect = CountVectorizer(tokenizer=tokenizer, ngram range=(1,2))
clf = SGDClassifier(loss='log', max_iter=100, tol=1e-6, random_state=42)
```

| Accuracy Score: 0.84609 | 43542150039 | | | |
|-------------------------|-------------|--------|----------|---------|
| | precision | recall | fl-score | support |
| Comparative Negligence | 0.57 | 0.20 | 0.30 | 911 |
| Fault unknown | 0.00 | 0.00 | 0.00 | 3 |
| Insured at fault | 0.87 | 0.96 | 0.91 | 9210 |
| | | | | |

0.83

total

| parative Negligence | 0.57 | 0.20 | 0.30 | 911 |
|---------------------|------|------|------|------|
| Fault unknown | 0.00 | 0.00 | 0.00 | 3 |
| Insured at fault | 0.87 | 0.96 | 0.91 | 9210 |
| No fault | 0.47 | 0.29 | 0.36 | 716 |
| ther party at fault | 0.84 | 0.83 | 0.84 | 3383 |
| | | | | |

0.85

0.83

14223

Key Features

Comparative Negligence: speed majority comp negligence lookout compneg decision comparative comp neg neg

Fault unknown: veh ticket report alexandria pc you pc to lessner insd or

Insured at fault: insd at from clmt iv ran liability adverse control single fol iv when iv into cv iv rear

No fault: a deer jetta lor shooting suspect markus comp theft shot deer

Other party at fault: liability denial rear endediv umpd ended iv accepted liability fol cv when cv cv rear struck iv umbi

```
Word2Vec
                                              0.5
                                                                                     damages
model.wv.most similar(positive='vehicle')
                                                                                    plate
[('had', 0.9995748400688171),
                                              0.0
 ('car', 0.999489963054657),
 ('insured', 0.9994364976882935),
 ('pole', 0.9993816614151001),
 ('iv', 0.9993693232536316),
 ('cut', 0.9993181824684143),
                                                                                             towed
                                             -0.5
 ('quitman', 0.9993139505386353),
 ('be', 0.9992308616638184),
                                                                                   phone
 ('services', 0.9992300271987915),
 ('he', 0.9992241859436035)]
                                             -1.0
                                                             2.5
                                                                     5.0
                                                                             7.5
                                                                                     10.0
                                                                                             12.5
                                                    0.0
```

Can you predict what group the claim should be routed to?

| Cleveland Field Ops PIP Tampa Field Ops Phoenix Casualty Ops Nashville Field Ops Nashville Casualty Ops Atlanta Casualty Ops Large Loss 2 Cleveland Casualty Ops CCU NARBI Tampa Casualty Ops Atlanta Field Ops Large Loss 1 Phoenix West Field Ops Albany Casualty Ops Total Loss Phoenix East Field Ops Claims Overflow Fast Track DMA Vendor Albany Field Ops Inbound Subrogation Recoveries Inactive Specialty Large Loss 3 Non Claims Central SIU Claims QA West Coast SIU TAG Premium Fraud SIU Field Ops 2 Executive CCU Executive Dispatch Admin | 9030 8537 5143 5130 4910 4213 3568 3262 3003 3002 2779 2528 2513 2396 2244 1969 1680 1634 1530 1390 1121 1095 887 508 449 389 319 305 264 195 134 39 87 111 | Field Ops Casualty Ops PIP Loss CCU NARBI Claims Overflow Fast Track DMA Vendor Inbound Subrogation Recoveries Inactive SIU Specialty Non Claims Claims QA TAG Dispatch Admin CCU Executive | 26587 20411 8537 7657 3002 2779 1530 1390 1121 887 508 449 406 389 305 195 39 | Field Ops Casualty Ops PIP Loss CCU NARBI | 26587 20411 8537 7657 3002 2779 |
|--|--|---|---|---|--|

```
vect = CountVectorizer(tokenizer=tokenizer, ngram_range=(1,2))
clf = SGDClassifier(loss='log', max_iter=100, tol=1e-6, random_state=42)
```

Accuracy Score: 0.8117915824619981

```
print(classification report(y test, y pred))
              precision
                          recall fl-score
                                              support
         CCU
                   0.84
                             0.67
                                       0.74
                                                  1012
Casualty Ops
                  0.86
                             0.86
                                       0.86
                                                 6702
   Field Ops
                  0.81
                             0.86
                                       0.84
                                                 8782
                  0.73
                            0.80
                                   0.76
                                                 2539
        Loss
                   0.82
                             0.56
                                       0.67
                                                  905
       NARBI
                   0.76
                             0.68
                                       0.72
                                                  2822
         PIP
                   0.81
                                       0.81
                                                22762
 avg / total
                             0.81
```

Key Features

CCU: ccu sol lit emailed plntf served pl pc suit revd

Casualty Ops: complete bie rept change of bie pc to pc attny ird rec clamnt eh

Field Ops: flags Im to ebi to ih closing ih called the for cb closing file expo

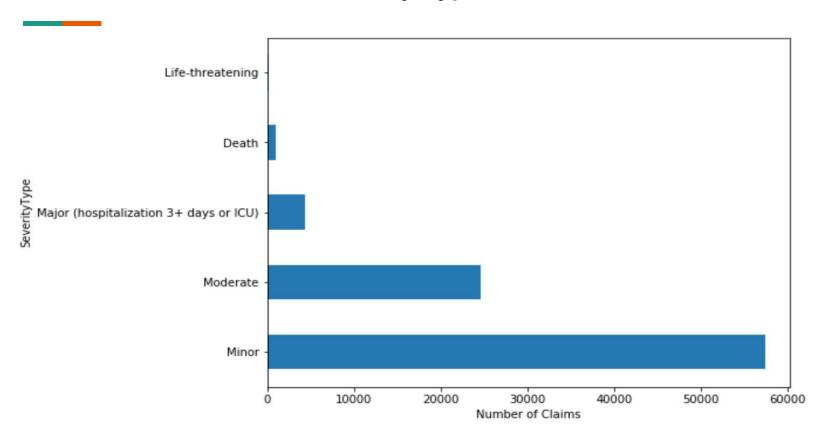
Loss: atc atty from atty i got dismissal ob call recommendations i called rcvd the only executed

NARBI: thanked wclmnt was able cnt placed phone call to lmtcb placed phone pat lmfcb

PIP: claim to medpay transfer transferring dilley aao oc ime pip sup to pip

Can you predict the severity type?

Severity Type



TFIDF & Multinomial Naive Bayes

: tfidf = TfidfVectorizer(stop words=stop words, ngram range=(2,3))

```
tfidf_train = tfidf.fit_transform(X_train.values)
tfidf_test = tfidf.transform(X_test.values)

nb_classifier.fit(tfidf_train, y_train)
pred = nb_classifier.predict(tfidf_test)

score = metrics.accuracy_score(y_test, pred)
print(score)
```

Stochastic Gradient Descent Classifier

```
X = model['ClaimLevelBody'].str.strip()
y = model['SeverityTypeName']
X train, X test, y train, y test = train test split(X, y, test size = 0.33, random state = 42)
def tokenizer(text):
    return re.findall(r'[a-z0-9]+', text.lower())
vect = CountVectorizer(tokenizer=tokenizer)
clf = SGDClassifier(loss='log', max iter=100, tol=1e-6, random state=42)
X train tfidf = tfidf.fit transform(X train)
X test tfidf = tfidf.transform(X test)
clf.fit(X train tfidf, y train)
y pred = clf.predict(X test tfidf)
np.mean(y test==y pred)
0.6740490754411869
```

Stochastic Gradient Descent Classifier

Accuracy Score: 0.6740490754411869

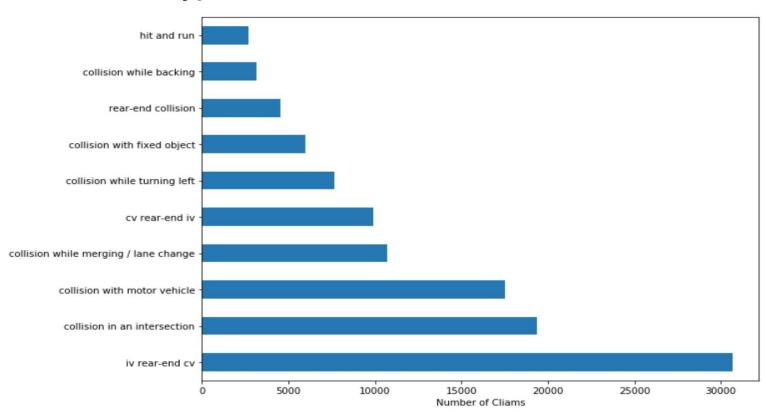
| Accuracy Score: 0.6/40490/54411869 | precision | recall | fl-score | support |
|--|-----------|-------------|-------------------|---------|
| | | ASSASSAS CA | ESERTO TECNESIONO | |
| Death | 1.00 | 0.04 | 0.08 | 136 |
| Life-threatening | 0.00 | 0.00 | 0.00 | 34 |
| Major (hospitalization 3+ days or ICU) | 0.61 | 0.17 | 0.27 | 716 |
| Minor | 0.69 | 0.98 | 0.81 | 9233 |
| Moderate | 0.48 | 0.11 | 0.18 | 4104 |
| avg / total | 0.63 | 0.67 | 0.59 | 14223 |

In [147]: print_top10(tfidf, clf, class_labels)

Death: wrongful killed news died funeral fatal death deceased fatality estate
Life-threatening: torrie ped lybarger life montgomery fx tawanda icu coma pedestrian
Major (hospitalization 3+ days or ICU): ribs excess hospitalized fractured uim broken hospital fx
surgery sir

Minor: minor atc tol attry rear sore ha lm claimant clamnt Moderate: head concussion office used wrist best purposes law er attorney Can you predict the loss cause?

Loss Cause Types



Preparing the Model

In [253]: loss_cause_df.head()

Out[253]:

| | CCCreateTime | AccidentDescription | DamageDescription | LossCauseName | LossCauseLabel | CombinedDescription |
|---|----------------------------|--|---|--|----------------|--|
| 0 | 2015-03-12 09:05:17.910 | the insured was test driving a vehicle the ov | left side damages towed by unknown none front | collision with motor vehicle | 3 | the insured was test driving a vehicle the ov |
| 1 | 2015-03-12 11:46:23.159 | the iv was driving down the road when the ov i | front right headlight front side of bumper dr | collision while merging / lane change | 4 | the iv was driving down the road when the ov i |
| 2 | 2015-03-12 13:12:35.444 | insured was stopped at the stop light when cv | unknown damages rear bumper trunk right rear | rear-end collision | 8 | insured was stopped at the stop light when cv |
| 3 | 2015-03-12 13:12:35.444 | insured was stopped at the stop light when cv | unknown damages rear bumper trunk right rear | rear-end collision | 8 | insured was stopped at the stop light when cv |
| 4 | 2015-03-12 13:12:35.444 | insured was stopped at the stop light when cv | unknown damages rear bumper trunk right rear | rear-end collision | 8 | insured was stopped at the stop light when cv |

Combined Description with CountVectorizer and Multinomial Naive Bayes

```
In [254]: X = loss cause df['CombinedDescription']
          y = loss cause df['LossCauseLabel']
          X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
In [255]: cv = CountVectorizer(stop words=stop words)
          count train = cv.fit transform(X train.values)
          count test = cv.transform(X test.values)
In [256]: nb classifier = MultinomialNB()
          nb classifier.fit(count train, y train)
          pred = nb classifier.predict(count test)
          score = metrics.accuracy score(y test, pred)
          print(score)
          0.6681948525507133
```

Combined Description with TFIDF and Multinomial Naive Bayes

Accident Description with CountVectorizer and Multinomial Naive Bayes

```
In [151]: X = loss cause df['AccidentDescription']
          y = loss cause df['LossCauseLabel']
          X train, X test, y train, y test = train test split(X, y, test size=0.2, random state=42)
In [152]: cv = CountVectorizer(stop words=stop words)
          count train = cv.fit transform(X train.values)
          count test = cv.transform(X test.values)
In [153]: nb classifier = MultinomialNB()
          nb classifier.fit(count train, y train)
          pred = nb classifier.predict(count test)
          score = metrics.accuracy score(y test, pred)
          print(score)
```

Accident Description with TFIDF and Multinomial Naive Bayes

Next Steps

- Word2Vec → Pre-Trained
- Acronym Substitution
- 2+ columns of text to predict
- Focus on Comparative Negligence

Questions?