Real-Time Risk Evaluation System for Aviation Safety

Saakaar Bhatnagar saakaar@stanford.edu , Nicolas Tragus ntragus@stanford.edu

https://youtu.be/o4oJxVlkbYE

What's new

We aim at improving aviation safety by creating a tool capable of assessing the risk of a developing situation in flight based on previous reports from pilots in such situations. The novelty of this is that the tool will **work in real-time**, with the pilot able to communicate with the algorithm.

Database

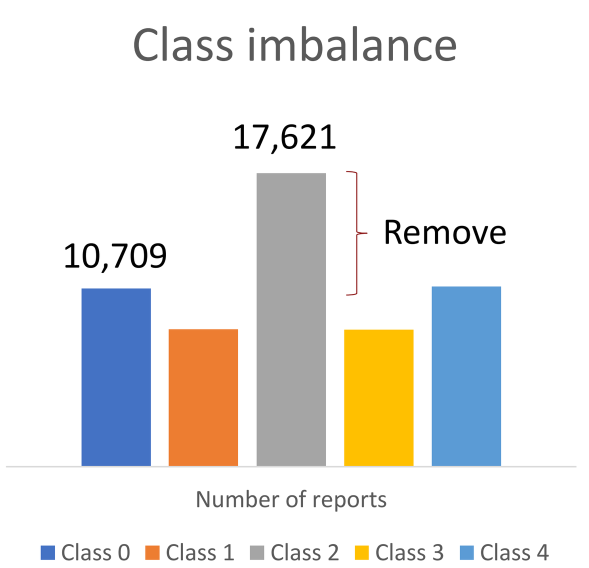
We take the data from the ASRS database: 210,000 accident reports on every type of planes in the US.

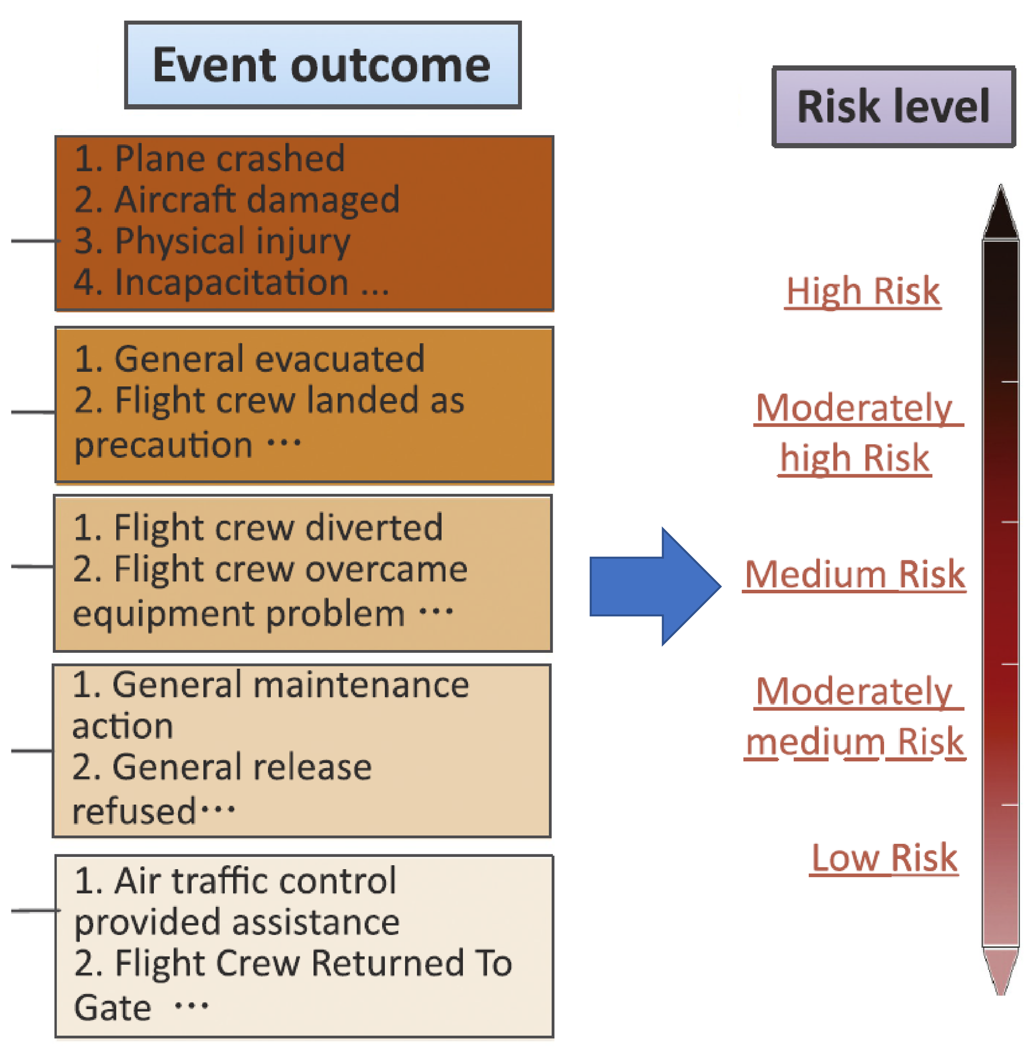
Input data used from the report (given as string):

- Situation
- Crew Size (integer)
- Narrative
- Weather
- Flight type
- Flight phase

We need to map every outcome of situation (e.g. aircraft damaged, general maintenance needed) to a one-hot encoded vector of size 5, to depict the risk categories in order to get a **classification problem**.

We notice we have a class imbalance issue. This leads the network to overpredict class 2 when testing



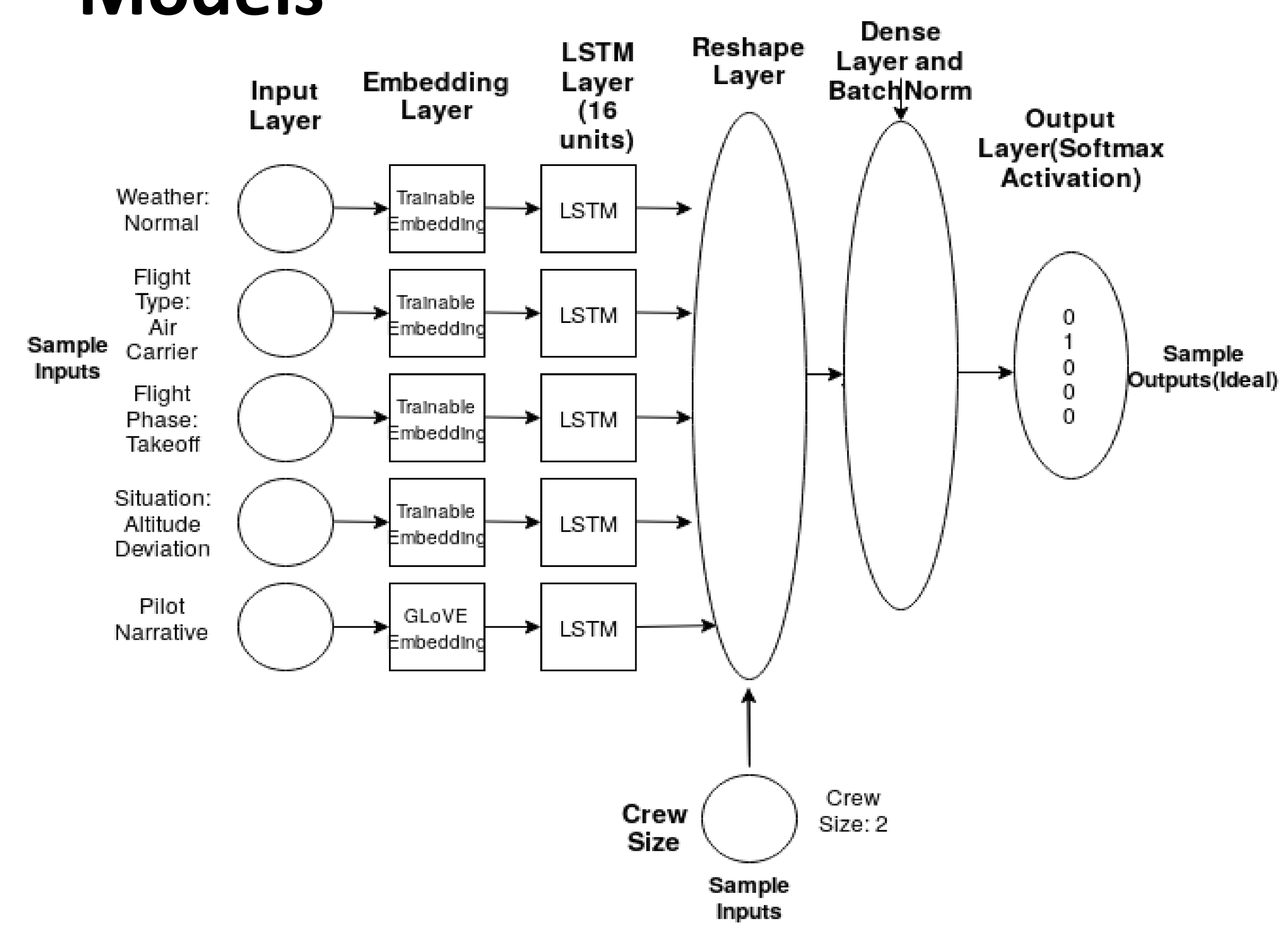


Data preprocessing

We are dealing with the categorical strings and the narrative separately.

- Remove Nan/junk in the data
- Tokenize the data passed as categorical string
- Pad the data with zeros and pass it on to the network

Models

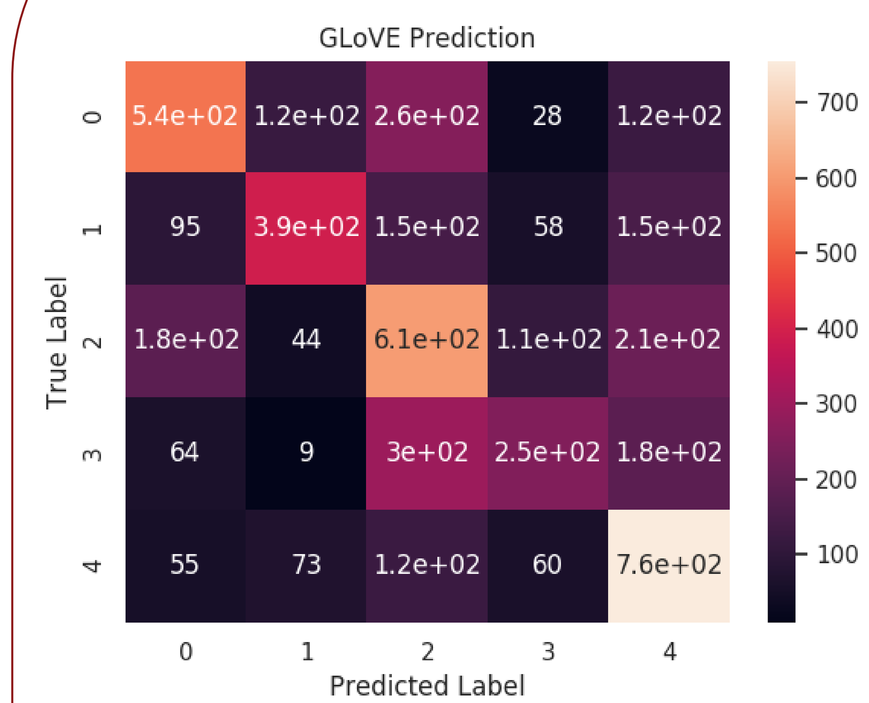


We tested **three types of architecture:**

- Sentiment score analysis of the narrative, based on 0,9*optimism calculated+0,1*subjectivity of narrative. Outputs a float for the narrative that can be used by the network
- Learn a word embedding for **every input** and pass it to the LSTM layer further down the network
- Use a pre-trained word embedding (GloVE) **for the narrative**. The other **categorical** text inputs still have a trainable embedding

We use an embedding layer followed by a couple of LSTM layers and dense layers, and the output is given by a softmax activation.

Results/Discussion



After class balancing, our confusion matrix has improved but isn't as diagonal as we would like.

As this is a safety application, we chose **recall** as our primary metric to optimize. The third algorithm performs better in that regard, especially for situation with a high-risk level.

The recall numbers obtained might seem relatively low but are due to two factors:

- High complexity of the problem: the same set of circumstances can lead to different outcomes
- Relatively high Bayes/Human error for the problem

Future work

A few ways to improve our algorithm:

- Add technical data to the input, such as speed of ascent/descent, engine revolution per minute, etc…
- The narrative used for training are in the past tense, but the pilots in real-time would use present, thus improving the language processing part could help improve the performances

References

[1] Xiaoge Zhang, Sankaran Mahadevan,"Ensemble machine learning models for aviation incident risk prediction", Decision Support Systems, Volume 116, January 2019, Pages 48-63, ISSN 0167-9236, https://doi.org/10.1016/j.dss.2018.10.009.

[2] A. Chanen, "Deep learning for extracting word-level meaning from safety report narratives," 2016 Integrated Communications Navigation and Surveillance (ICNS), Herndon, VA, 2016, pp. 5D2-1-5D2-15.