Rega

Improving rescue helicopter dispatch decisions

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In collaboration with: Rega
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Executive Summary / Abstract

In Switzerland, people hike a lot and in a normal year 20,000 people are injured and almost 40 incidents per year are fatal. That's why Rega, the Swiss air rescue team, is constantly striving to make its rescue service faster and more reliable. Based on a patient's location, our Lasso model, trained on previous missions, predicts how long it would take each helicopter to reach the destination and then sends the fastest one.

Expected impact

By integrating new data sources into Rega's existing system and then training a machine learning model to make informed dispatch decisions, we aim to bring medical help to patients faster and thus save more lives.

Approach

Building upon the previous Rega team's work for Hack4Good 2020, we implemented a Lasso model that, given a patient's location and a helicopter's position, predicts how long it would take the helicopter to reach the patient's location.

To train our model, a data frame (see Table 1) was created from two data sources: historical helicopter positions and historical missions information. From these datasets, we have extracted features such as takeoff positions/times and the arrival positions/times that allowed us to obtain relevant distance features. Additionally, third-party APIs were used to create topography and weather features.

Our target variable, the "time to patient", was calculated using the features extracted above and represents the time it took the helicopter, after receiving the alarm, to reach a two-kilometer radius around the patient's location.
### Distance features

<table>
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<th>Distance</th>
<th>Delta Latitude</th>
<th>Delta Longitude</th>
<th>Climb</th>
<th>Descent</th>
<th>Vertical Travel Distance</th>
<th>Visibility</th>
<th>Heavy Clouds</th>
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</table>

Table 1: Overview features

### Difficulties, Limitations & Risks

One of the objectives of this project was to make real-time predictions. To this end, Rega gave us access to their data lake which collects live positions of their helicopters. However, it turned out that querying the data was problematic because the data lake returned a different number of results each time a query was executed. After several attempts to solve this problem, we decided together with Rega to focus on the other objectives.

In order to improve our predictions, we considered using weather data as well. However, we ran into the problem of the availability of high quality weather data. Therefore, we were only able to use METAR data from Swiss airports near the helicopter’s take-off position. It would have made sense to also include weather data from along the route from the base to the patient. However, retrieving METAR data proved to be tricky as the number of API calls per minute was restricted.

### Results & Deliverables

Our deliverables consist of two parts: a notebook in which features are extracted and models evaluated, and a web page that uses an API to display the results graphically.

Figure 1 shows a comparison between a baseline model, called the physical model, and our best-performing machine learning model. The latter is a simple approximation of a human decision, that is just the time computed from the average speed of a helicopter and the distance from the liftoff to the patient. The histogram shows the distribution of errors as well as the two-minutes threshold. Together with Rega, we decided that a prediction can be considered to be “correct” if the error is not greater than two minutes.

Our model outperforms the baseline model and increases the accuracy of predictions by about 15%, from about 66% to 81%. These results can be replicated using the notebook that is part of our deliverables. It also allows us to improve functionality or re-run the code when new data becomes available.
In order to make the predictions more accessible, an API allows the user to select a hypothetical patient location and historical time. The API then displays the three fastest helicopters with their estimated travel time on a map (see Figure 2).

**Figure 2: Screenshot of the API**

**Recommendations & Conclusion**

In conclusion, this project was a step closer to a model that can help Rega make better dispatch decisions by improving the accuracy of time to patient predictions by approximately 15%. We designed the code so that anyone can reproduce and improve it. The notebook is structured and documented so that it can be run (with correct dataframes) without any problems. We hope that this can be used to go further easily and here are some recommendations.

This project could be taken a step further by trying again to use the live positions of the helicopters and thus make real-time decisions. One could then filter on the live status of the helicopters to consider only those that are available at a given time.

Moreover, the features could also be improved. For example, to improve the weather features, one could take into account not only the weather at takeoff but also along the route and even the forecast for the following hour. As for the elevation feature, helicopters do not necessarily have to fly in a straight line, and can therefore be optimized by using a more realistic route.

Finally, other data sources could be explored such as seasonality, as the traffic differs in winter and in summer.