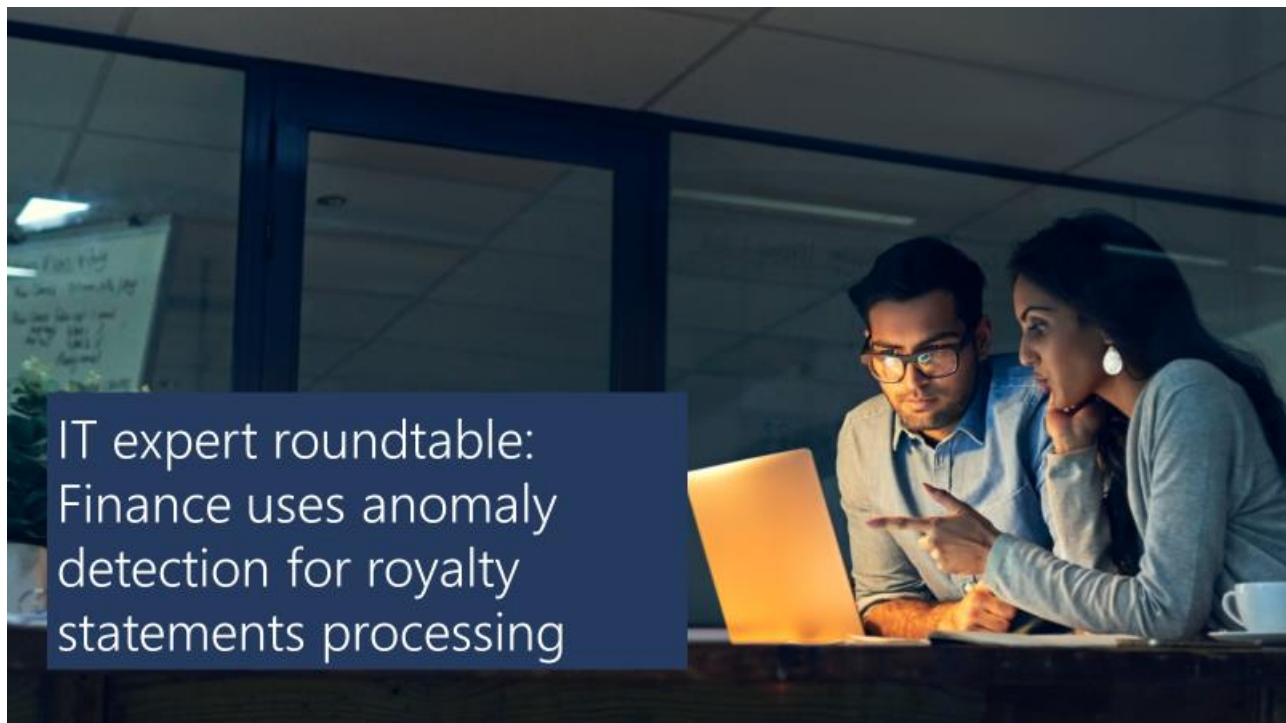


**QUESTION:**

What type of sponsorship did you have for this project?

ANSWER:

Because there was so much time spent on the manual approval of statements that are considered “low risk”, there was an appetite at the GM level to automate the approval process. In order to get the auto-approve process approved, we had to make sure that the solution was equal - or better - than the manual approval process.

QUESTION:

How much domain knowledge did the engineering team have when you started this project?

ANSWER:

We had good domain knowledge before the start of this project, but we also engaged with the business partners to understand what they do manually to perform the reconciliation and how they detect anomalies. This way it helped us to think broadly and design a solution which automated the process easily.

QUESTION:

Were you able to do much automation around your SOX controls?

ANSWER:

Yes, we were able to automate the SOX control. Leveraging Machine Learning with SOX control is new within our area. The main concern was the having Machine Learning continue to learn and imply new/modified rules. This is a scary area for compliance. Our machine learning is adjusting based on historical royalty's payout trends. We also added a reconciliation feature, so that we have confidence that the anomalies our Machine Learning identifies also has defined reconciliation rules in order for statements to be auto approved.

QUESTION:

You talked about being able to reduce the number of variables used in your machine learning model. How many did you start with and end with and how did you manage to reduce them?

ANSWER:

We were hit with the curse of dimensionality. We had a number of features that resulted in a large number of columns and samples. This model became complex pretty quickly. Correlation matrices, and a few other tools, helped us to understand how each attribute influenced the other. Using that, we reduced the number of dependent variables – from 30 down to 17. We managed the rows with scenario classification.

QUESTION:

How long did you pilot this solution before implementing it in production?

ANSWER:

For RAD (Royalty Anomaly Detection) we piloted it for 6 months. During this time we allowed our stakeholders to provide feedback to train the model. For the entire solution RAD RECON to auto-approval, we put into parallel production for 2 months to ensure that the decisions being made by the solution aligned to the manual approval process.

QUESTION:

While performing Machine Learning, how much data do you use for the training model and how often do you train the model?

ANSWER:

We followed the general split of 80:20 for training and testing. We used 24 months of data for the lookup. We have reviews setup and we re-evaluate and re-train the model if needed. So far we have done that twice.

For more information

Microsoft IT Showcase

microsoft.com/itshowcase

[Finance uses anomaly detection and automation to transform royalty statements processing](#)

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