Ensuring Fairness in Fraud Detection Process using Network Analytics

Luiz Kauffmann and Aline Riquetti

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Ensuring Fairness in Fraud Detection Process using Network Analytics

Luiz Kauffmann, SAS

Luiz Kauffmann has 15 years of experience in the Risk Industry, before joining SAS Luiz held various positions from Risk and Fraud Quantitative modeler in Experian and International Banks developing Fraud Detection Models, Credit And Market Risk Models and Debt Collection Models.

Aline Riquetti, SAS

Aline Riquetti, an experienced data scientist, brings nine years of expertise in data analysis and modeling for government agencies. With a focus on fraud, abuse and waste prevention projects, she has successfully contributed to both public and private sectors.

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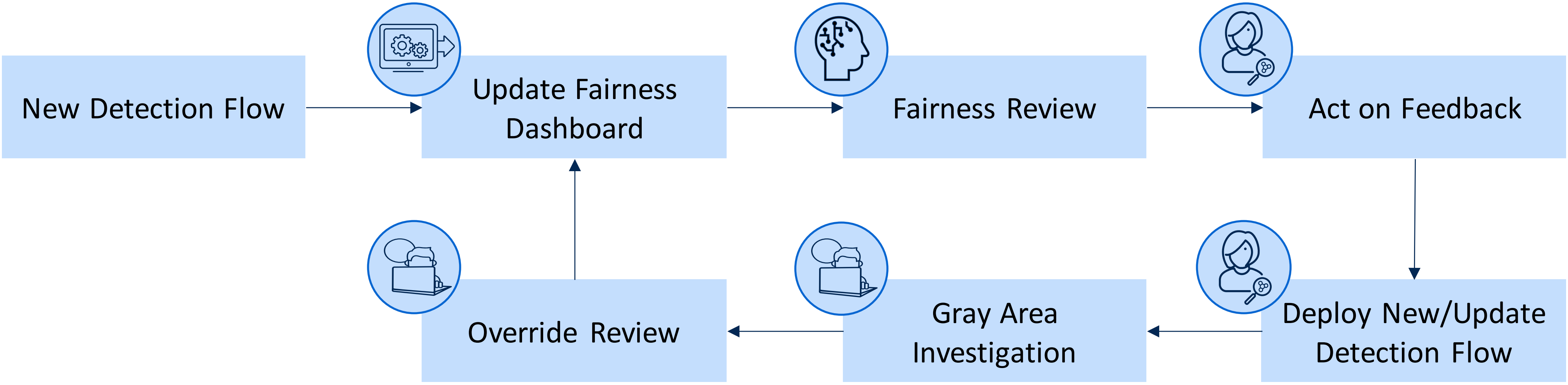
Solution Workflow

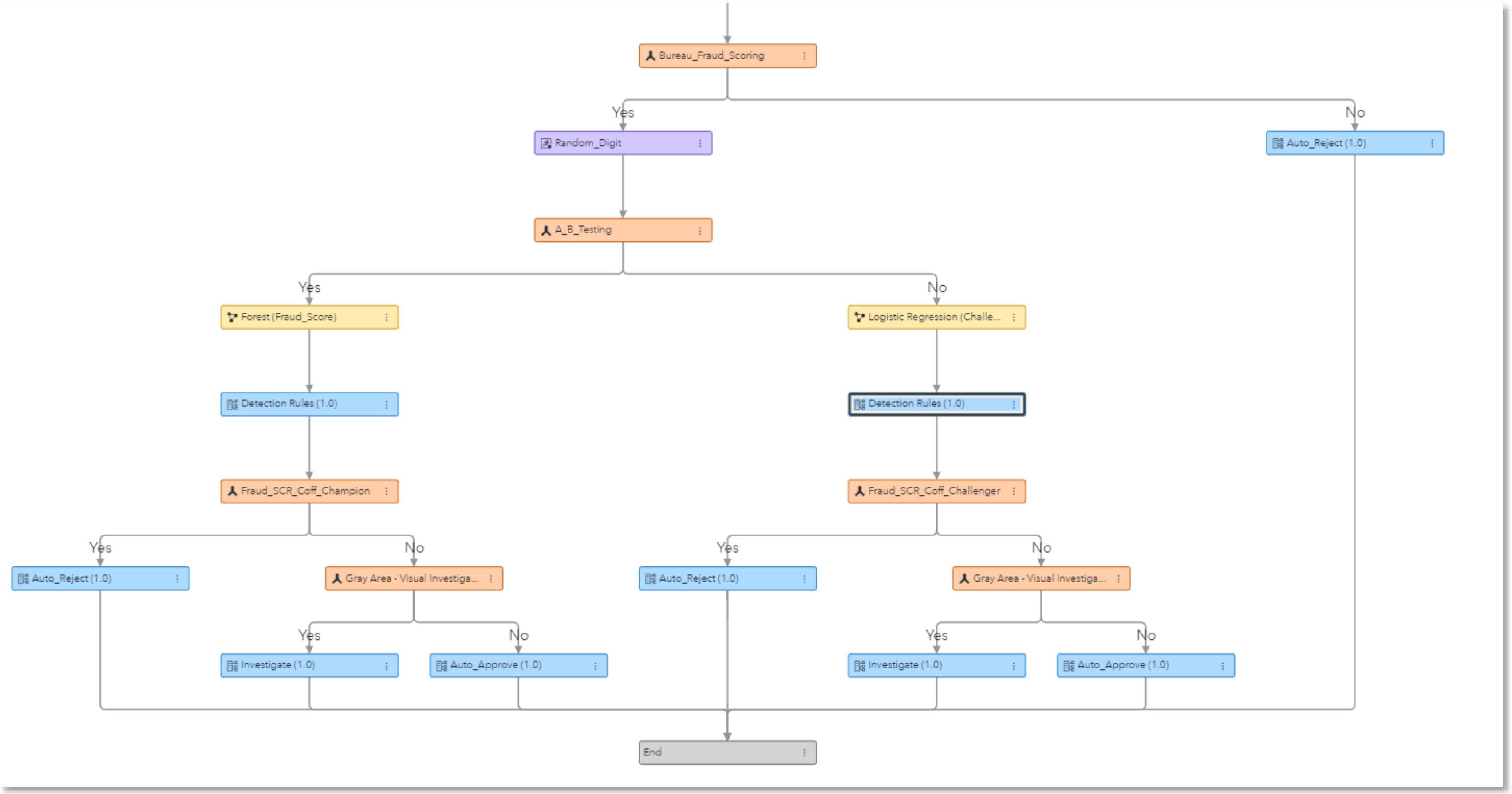


Trustworthy AI Specialist | Automated Task | Fraud Detection Scientist | Investigation Analyst

Demo

Ensuring Fairness in Fraud Detection Process using Network Analytics

Common Loan Origination/Application Flow



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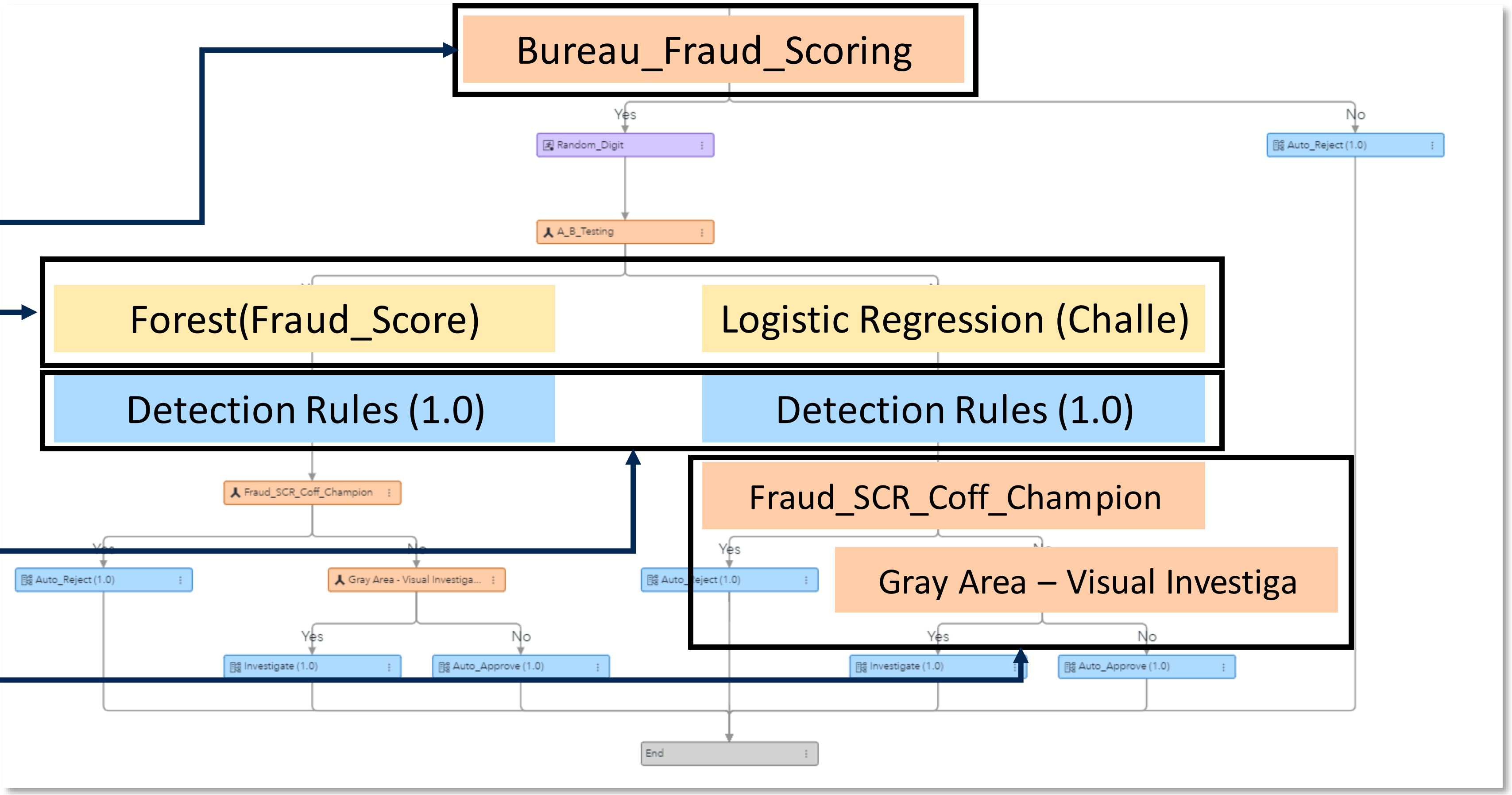
Common Loan Origination/Application Flow

Potential Bias Sources

- External Bureau Scoring and Information
- Machine Learning Model using internal and external data
- Business Detection Rules
- Gray Area – Scoring Threshold



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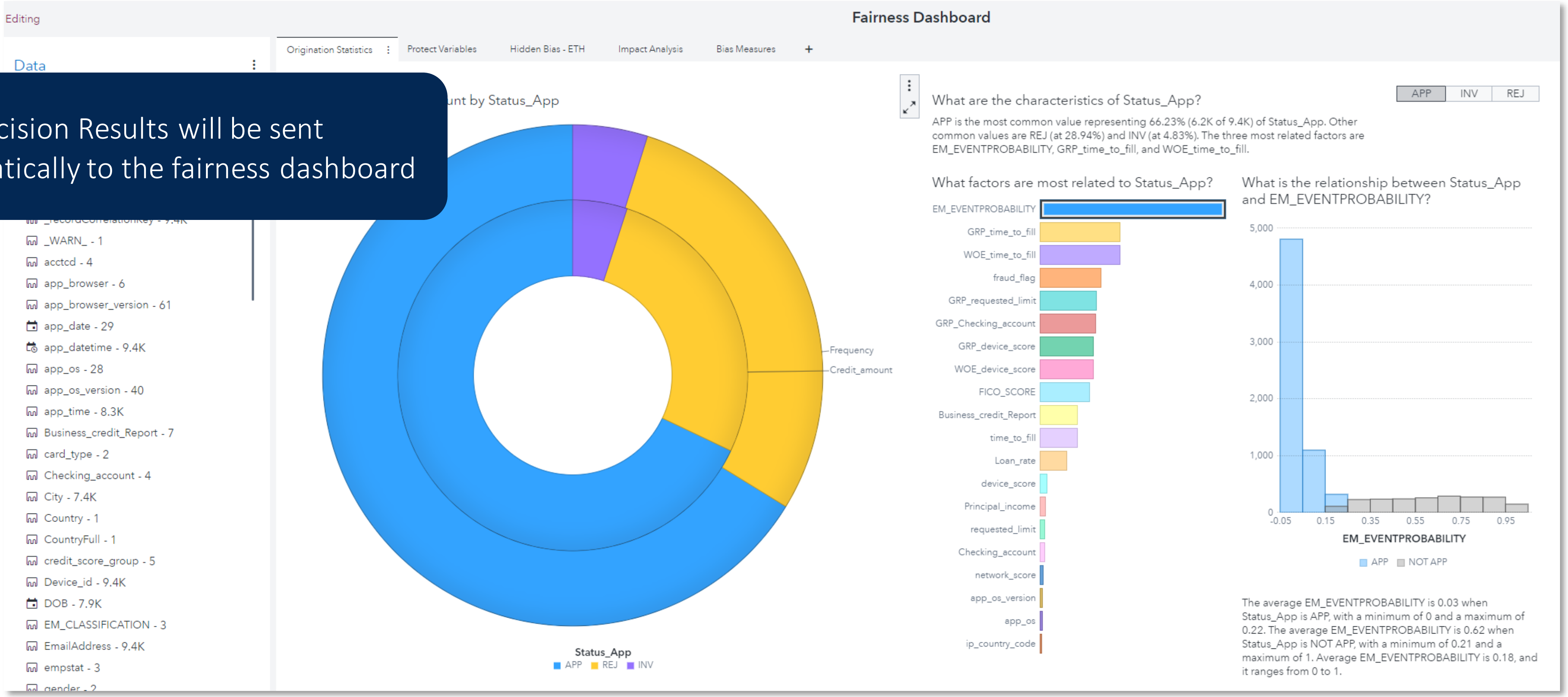
The Decision Results will be sent automatically to the fairness dashboard



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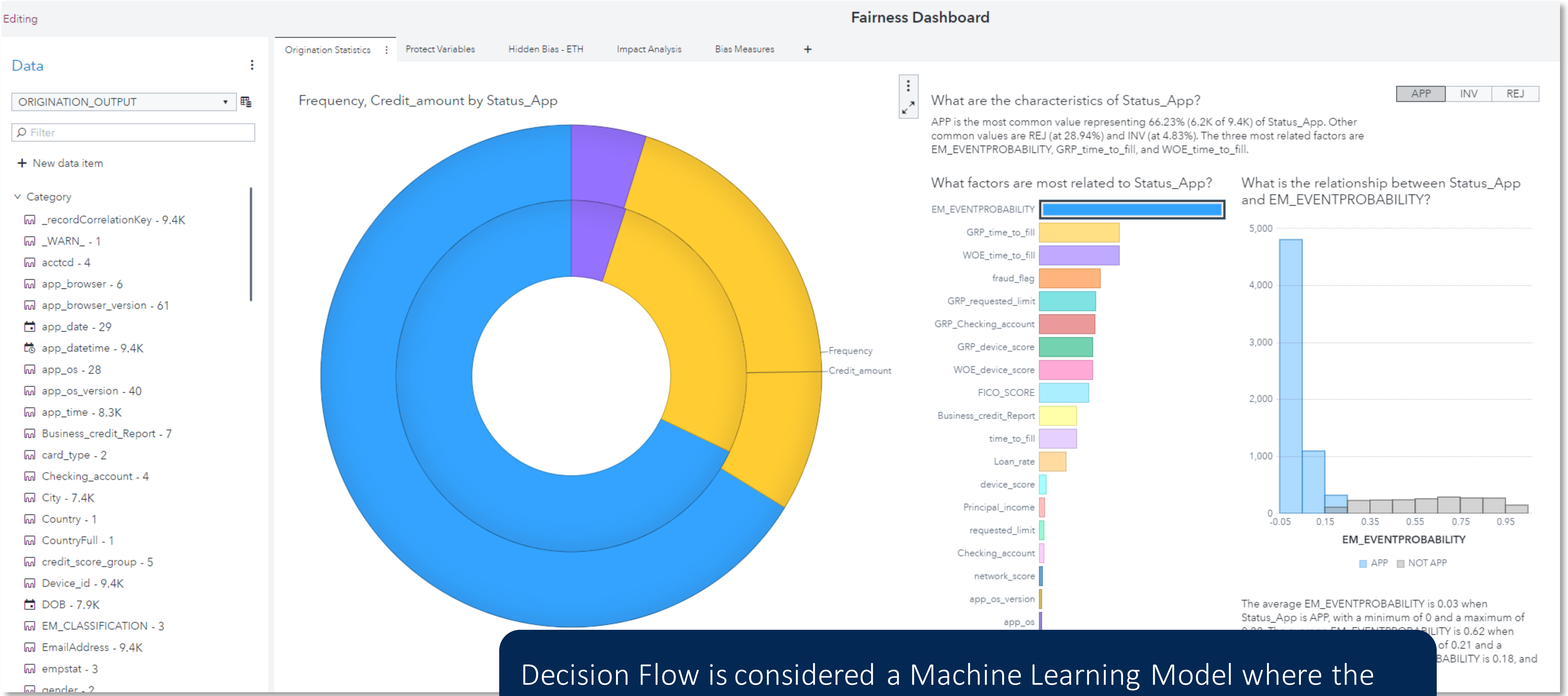

Decision Flow is considered a Machine Learning Model where the Target Variable is *Status Credit : Approved / Rejected*

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The Dashboard allows the import of protected variables to evaluate potential Hidden Bias

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The approval rate for every protected variable category

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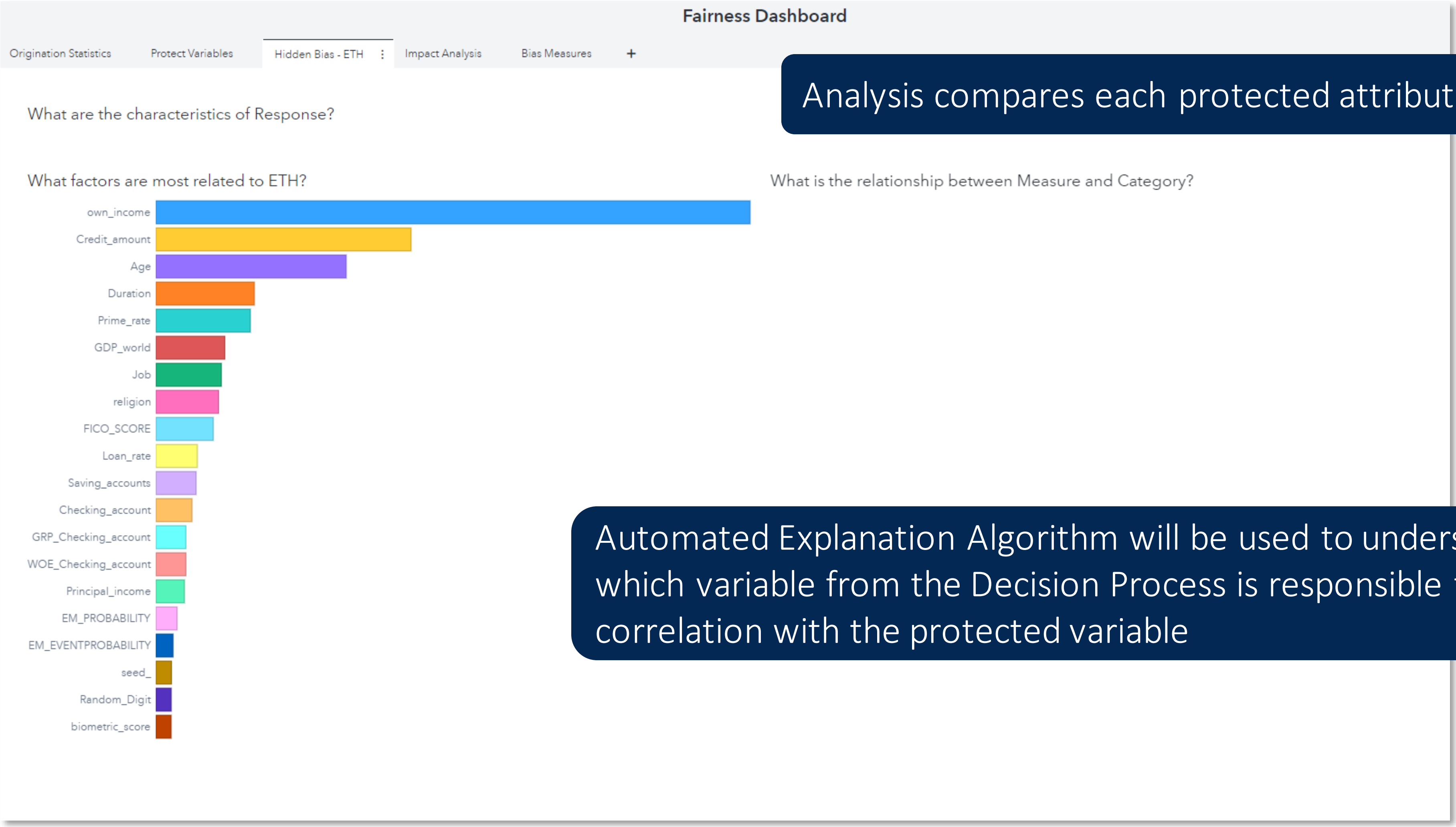

Analysis compares each protected attribute category

Automated Explanation Algorithm will be used to understand which variable from the Decision Process is responsible for the correlation with the protected variable

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Lending Statistics | Hidden Bias - Protected Variables | Hidden Bias - ETH | Hidden Bias - Religion | Hidden Bias - Region | Bias Statistics | Group Statistics | Diff Statistics | Trade - off Analysis with Interactive Tree | Counterfactual Analysis | Explain Rejected | +

- [x] ETH
- [ ] Gender
- [ ] REGION
- [ ] religion

Bias Statistic Value	senVar	Note	Compare Level	Bias Statistic Label	Bias Statistic	Ba
0.0449	ETH		HIS	Equal Opportunity	EqualOpportunity	AF
0.0848	ETH		WH	Equal Accuracy	EqualAccuracy	HI
0.0252	ETH		HIS	Predictive Parity	PredictiveParity	W
0.0699	ETH	Max FPR difference is greater than max TPR difference.	HIS	Equalized Odds	EqualizedOdds	W
0.0584	ETH		HIS	Demographic Parity (Statistical Parity)	DemographicParity	W

Group	senVar	Area Under ROC	False Negative Rate	False Positive Rate	Frequency Percent	Frequency	C
WH	ETH	0.5853	0.8824	0.0842	25.00%	1	
HIS	ETH	0.6861	0.9	0.0143	25.00%	1	
AS	ETH	0.6507	0.8704	0.0313	25.00%	1	
AF	ETH	0.6818	0.8551	0.022	25.00%	1	

Out of the box Bias Measures

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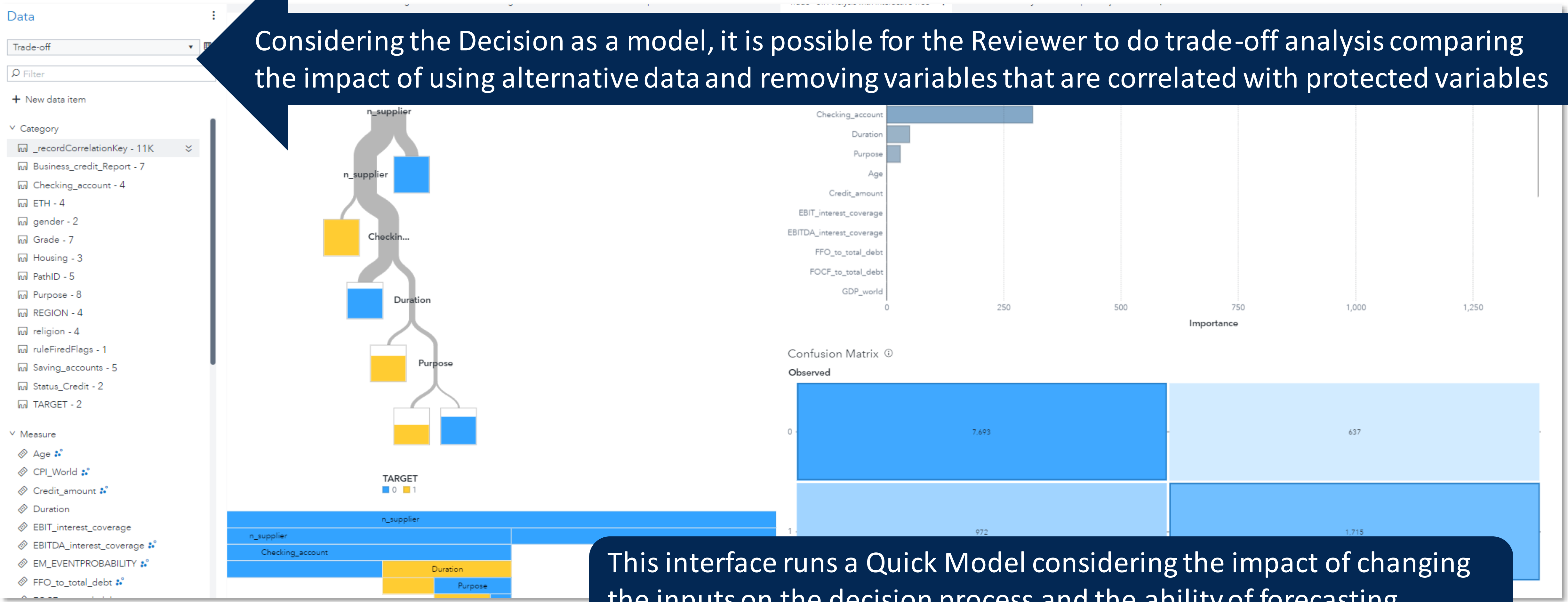

Considering the Decision as a model, it is possible for the Reviewer to do trade-off analysis comparing the impact of using alternative data and removing variables that are correlated with protected variables

This interface runs a Quick Model considering the impact of changing the inputs on the decision process and the ability of forecasting delinquent/riskier customers

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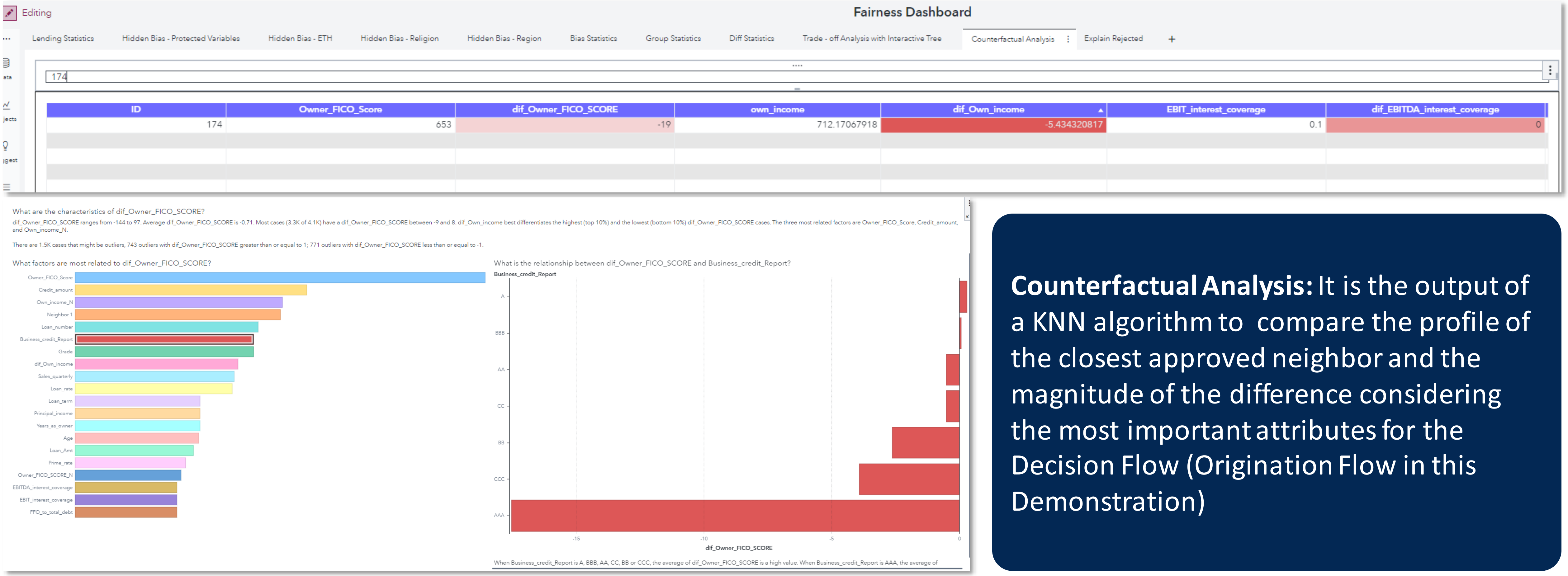

Counterfactual Analysis: It is the output of a KNN algorithm to compare the profile of the closest approved neighbor and the magnitude of the difference considering the most important attributes for the Decision Flow (Origination Flow in this Demonstration)

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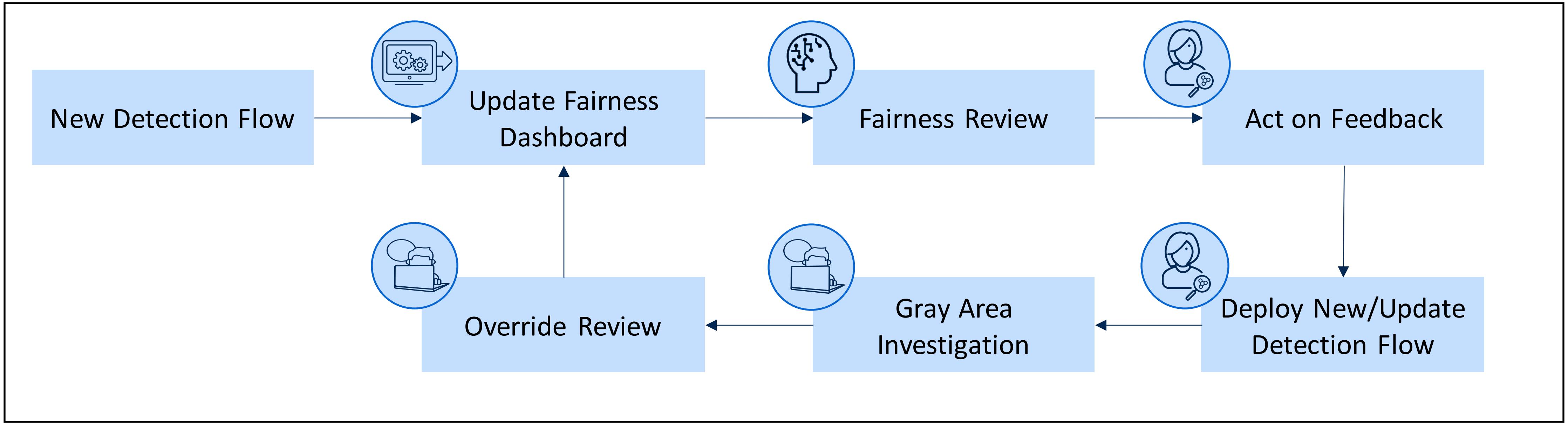
Solution Workflow



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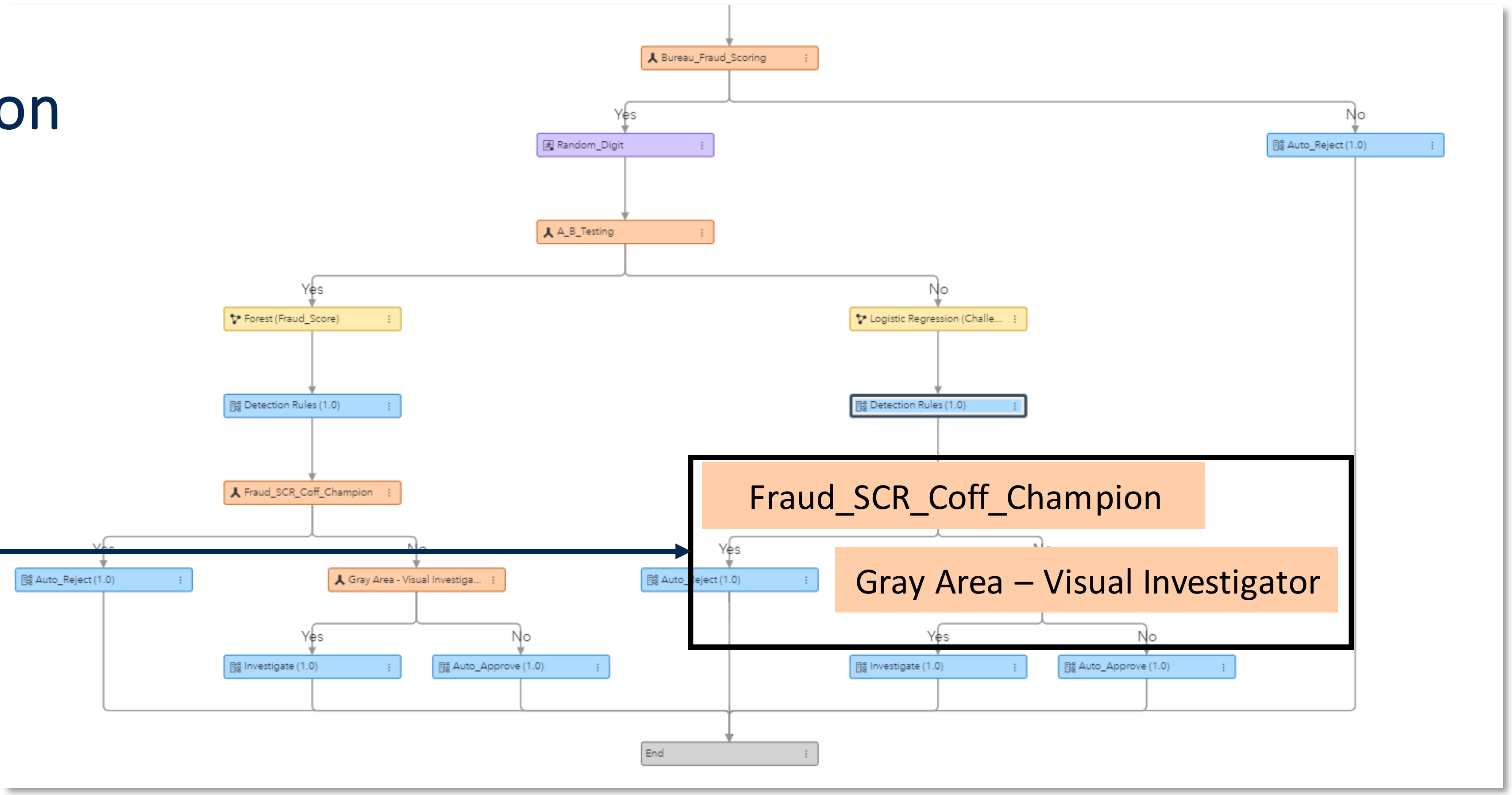
Common Loan Origination/Application Flow

Gray Area - Investigation

How to Manage the Gray Area Investigation in the Fairness perspective?



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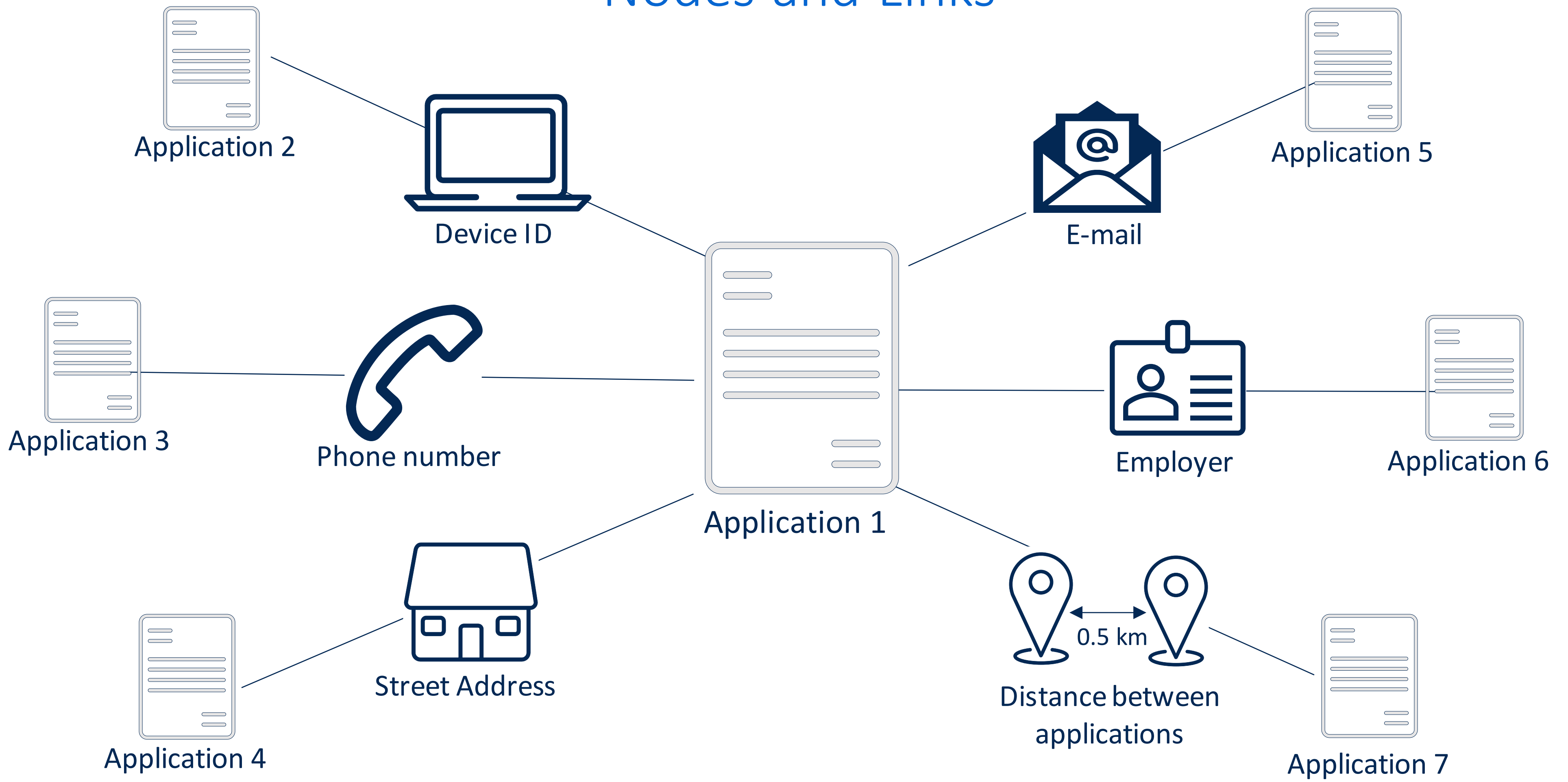
Nodes and Links



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In cases where we can’t conclude about the presence of fraud, could we use the existent relationships to classify an application?

"Tell me who your friends are, and I'll tell you who you are."

But is this always true, or just another way to perpetuate the bias in my decision?

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An introduction to the concept of homophilic networks.

- Homophily is a concept borrowed from sociology, and means that **people have a strong tendency to associate with others whom they perceive as being similar to themselves** *in some way* (Newman 2010)

- So, we define a homophilic network as a **network where fraudsters are more likely to be connected to other fraudsters**, and legitimate people are more likely to be connected to other legitimate people.

- In a **non-homophilic network**, people associate each other regardless of their labels, thus generating **many <u>cross-labeled edges</u>**, that is, an edge between a fraudster and a legitimate node. In a **homophilic network the proportion of cross-label edges is less than would be expected in a random network**.

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Checking if my network is homophilic

In a random network we would expect that the proportion of cross-labeled edge is:

$2 \times Nodes\ with\ a\ legitimate\ label\ (l)\ x\ Nodes\ with\ a\ fraud\ label\ (f)$ -> $2 \times l \times f$

In a random network the proportion of cross-labeled edges is:

Obs	random_network
1	0.36662

In our network the proportion of cross-labeled edge is:

The fraction of cross-labeled edge in this network is:

Obs	prop_cross_labeled
1	0.23147

Since the observed proportion of cross-labeled edges is less than the expected proportion in a random network, then, the null hypothesis $H_0$is rejected with a significance level of α=0.05. **That is, our network IS HOMOPHILIC!!**

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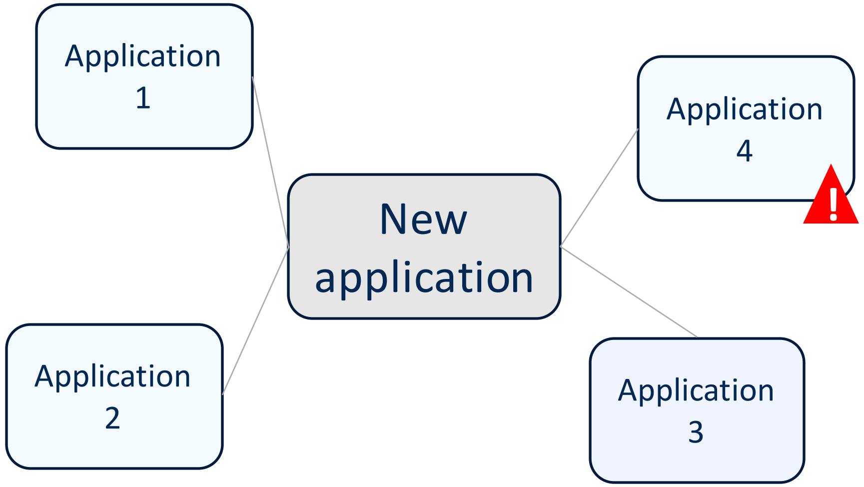
Relational Neighbor Classifier

My network is homophilic. And now, how to infer guilt to an application based on its connections (guilt-by-association)?



$$P(Fraud) = \frac{Fraudulent\ direct\ nodes}{Direct\ Nodes}$$

$$P(Fraud) = \frac{1}{4} = 0{,}25$$

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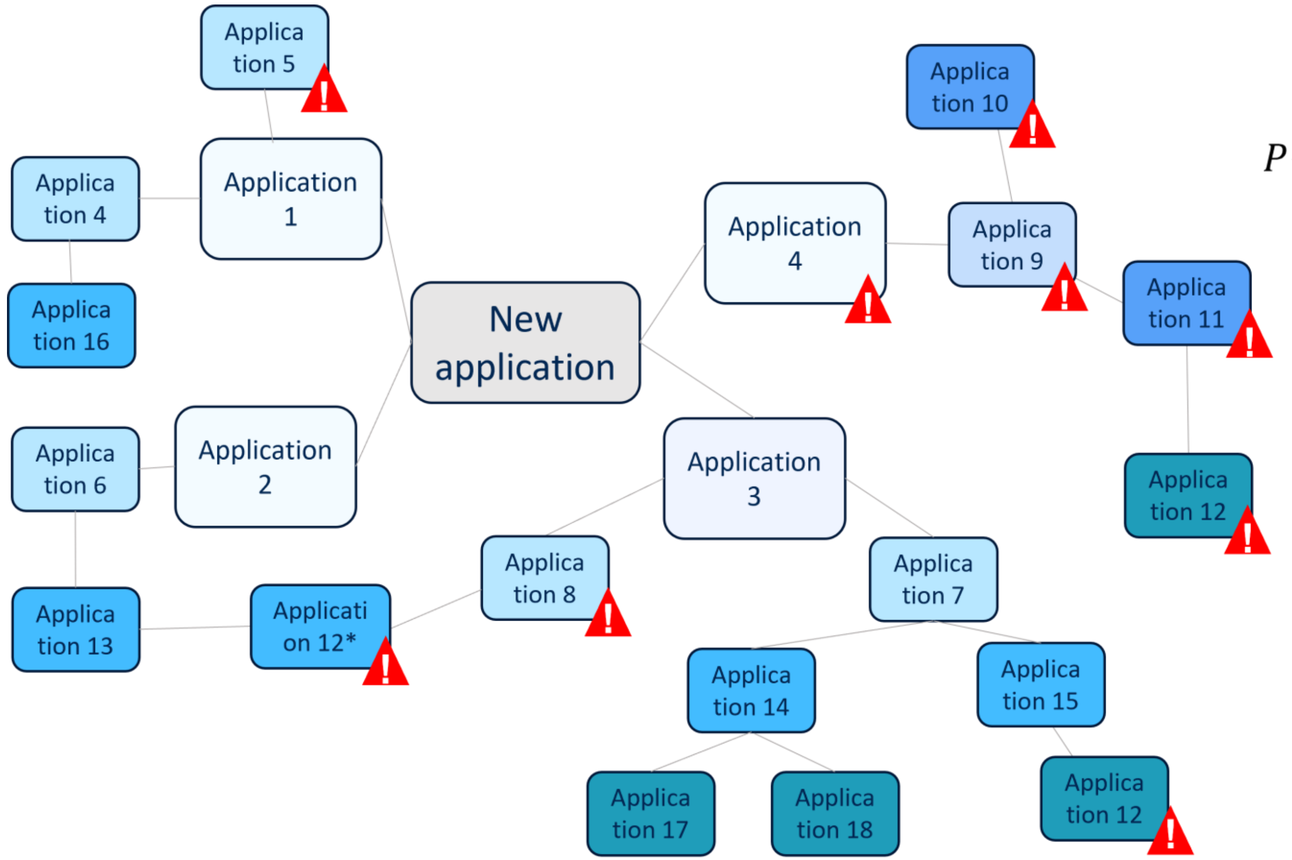
Expanded Relational Neighbor Classifier

Is it only the first-level relationships that matter for classifying an entity?



$$P(Fraud) = \frac{\sum_{i=1}^{max\ dist} w_i \times \frac{Fraudulent\ nodes\ in\ distance\ i}{Nodes\ in\ distance\ i}}{\sum_{i=1}^{max\ dist} w_i}$$

$$where\ \ w_i = \frac{1}{distance\ i}$$

$$P(Fraud) = \frac{\left(\frac{1}{1}\times\frac{1}{4}\right)+\left(\frac{1}{2}\times\frac{3}{6}\right)+\left(\frac{1}{3}\times\frac{3}{7}\right)+\left(\frac{1}{4}\times\frac{2}{4}\right)}{\frac{1}{1}+\frac{1}{2}+\frac{1}{3}+\frac{1}{4}}$$

$$P(Fraud) = \frac{(1/4)+(3/12)+(3/21)+(2/16)}{\frac{1}{1}+\frac{1}{2}+\frac{1}{3}+\frac{1}{4}}$$

$$P(Fraud) = 0{,}3685$$

*If there are multiple paths between 2 nodes, then the shortest path is used.

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Expanded Relational Neighbor Classifier

```
proc network
   links = public.application_links;
   linksVar
      from = from_application
      to = to_application;
   shortestPath
      outPaths    = PUBLIC.SHORTPATH;
run;
```

Expanded Relational Neighbor Classifier

Obs	APPLICATION_ID	EXPANDED_ERNC
1	17482741	0.667
2	3059607895	0.818
3	3748403515	0.667
4	3766289313	0.887
5	4805242533	0.818
6	5283601049	0.667
7	5457417795	0.951
8	6256254723	0.667
9	9440549304	0.667
10	520605627	0.545
11	1506416170	0.818
12	4463460927	0.545
13	5371881428	0.620
14	5430370092	0.880
15	5433988793	0.818

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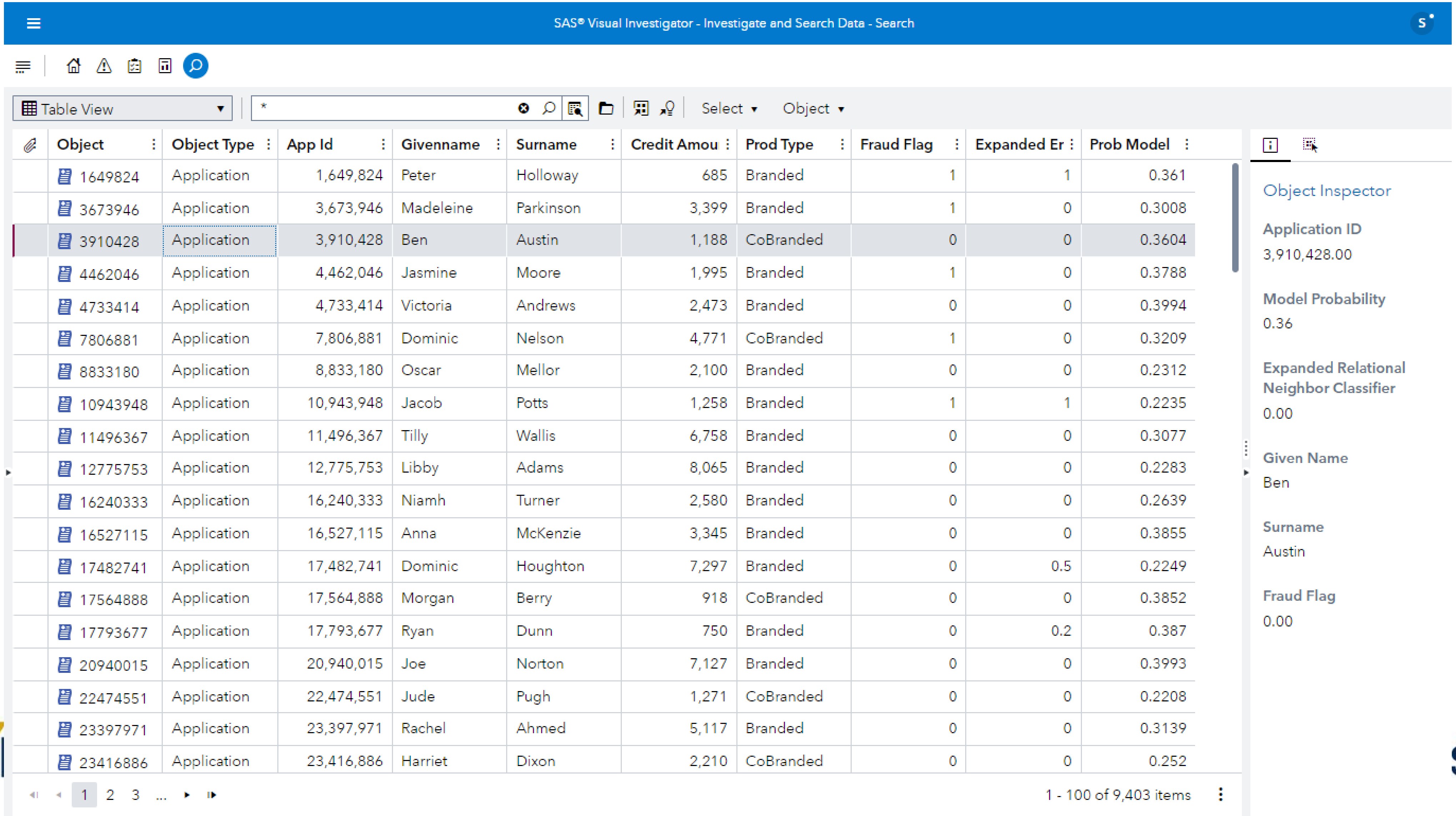
Visual Investigator



Object	Object Type	App Id	Givenname	Surname	Credit Amou	Prod Type	Fraud Flag	Expanded Er	Prob Model
1649824	Application	1,649,824	Peter	Holloway	685	Branded	1	1	0.361
3673946	Application	3,673,946	Madeleine	Parkinson	3,399	Branded	1	0	0.3008
3910428	Application	3,910,428	Ben	Austin	1,188	CoBranded	0	0	0.3604
4462046	Application	4,462,046	Jasmine	Moore	1,995	Branded	1	0	0.3788
4733414	Application	4,733,414	Victoria	Andrews	2,473	Branded	0	0	0.3994
7806881	Application	7,806,881	Dominic	Nelson	4,771	CoBranded	1	0	0.3209
8833180	Application	8,833,180	Oscar	Mellor	2,100	Branded	0	0	0.2312
10943948	Application	10,943,948	Jacob	Potts	1,258	Branded	1	1	0.2235
11496367	Application	11,496,367	Tilly	Wallis	6,758	Branded	0	0	0.3077
12775753	Application	12,775,753	Libby	Adams	8,065	Branded	0	0	0.2283
16240333	Application	16,240,333	Niamh	Turner	2,580	Branded	0	0	0.2639
16527115	Application	16,527,115	Anna	McKenzie	3,345	Branded	0	0	0.3855
17482741	Application	17,482,741	Dominic	Houghton	7,297	Branded	0	0.5	0.2249
17564888	Application	17,564,888	Morgan	Berry	918	CoBranded	0	0	0.3852
17793677	Application	17,793,677	Ryan	Dunn	750	Branded	0	0.2	0.387
20940015	Application	20,940,015	Joe	Norton	7,127	Branded	0	0	0.3993
22474551	Application	22,474,551	Jude	Pugh	1,271	CoBranded	0	0	0.2208
23397971	Application	23,397,971	Rachel	Ahmed	5,117	Branded	0	0	0.3139
23416886	Application	23,416,886	Harriet	Dixon	2,210	CoBranded	0	0	0.252

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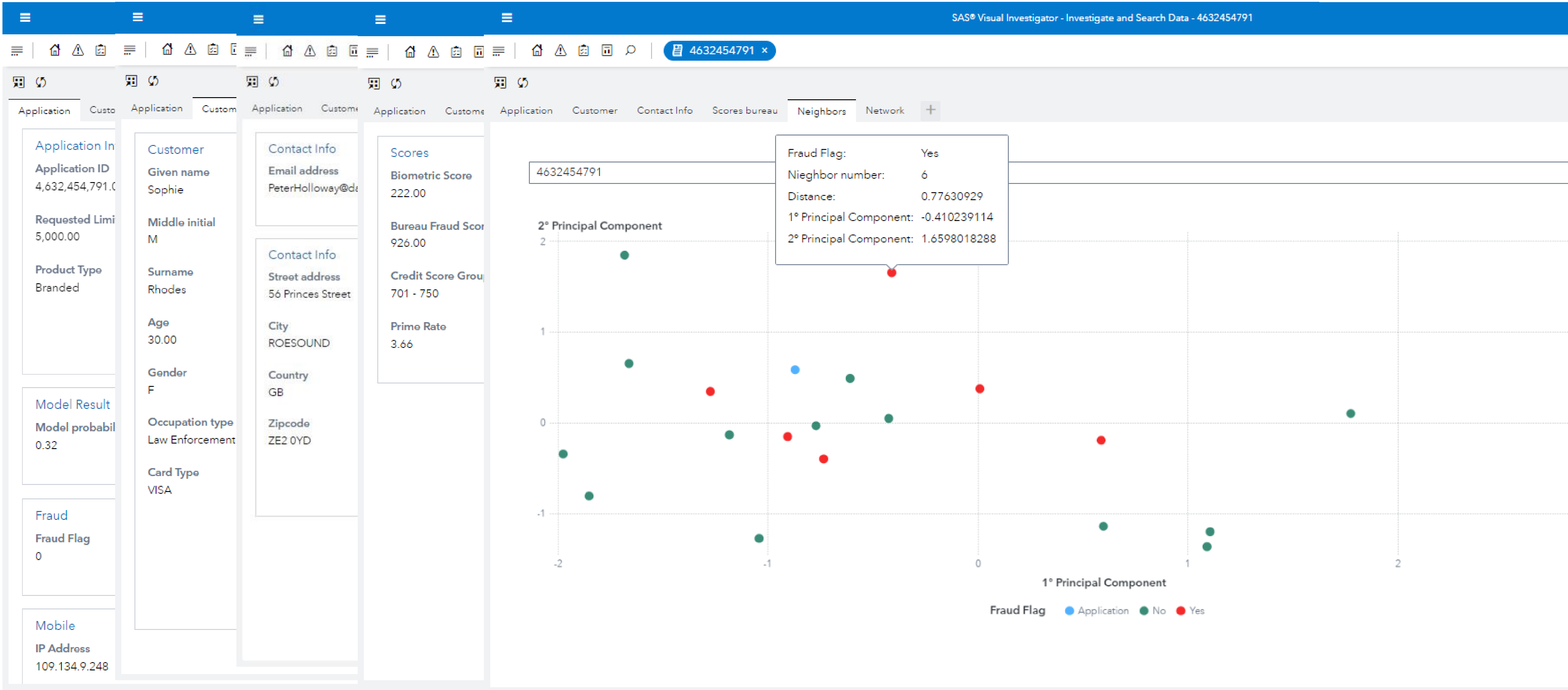
Relationship Network: a matrix to calculate proactive networks



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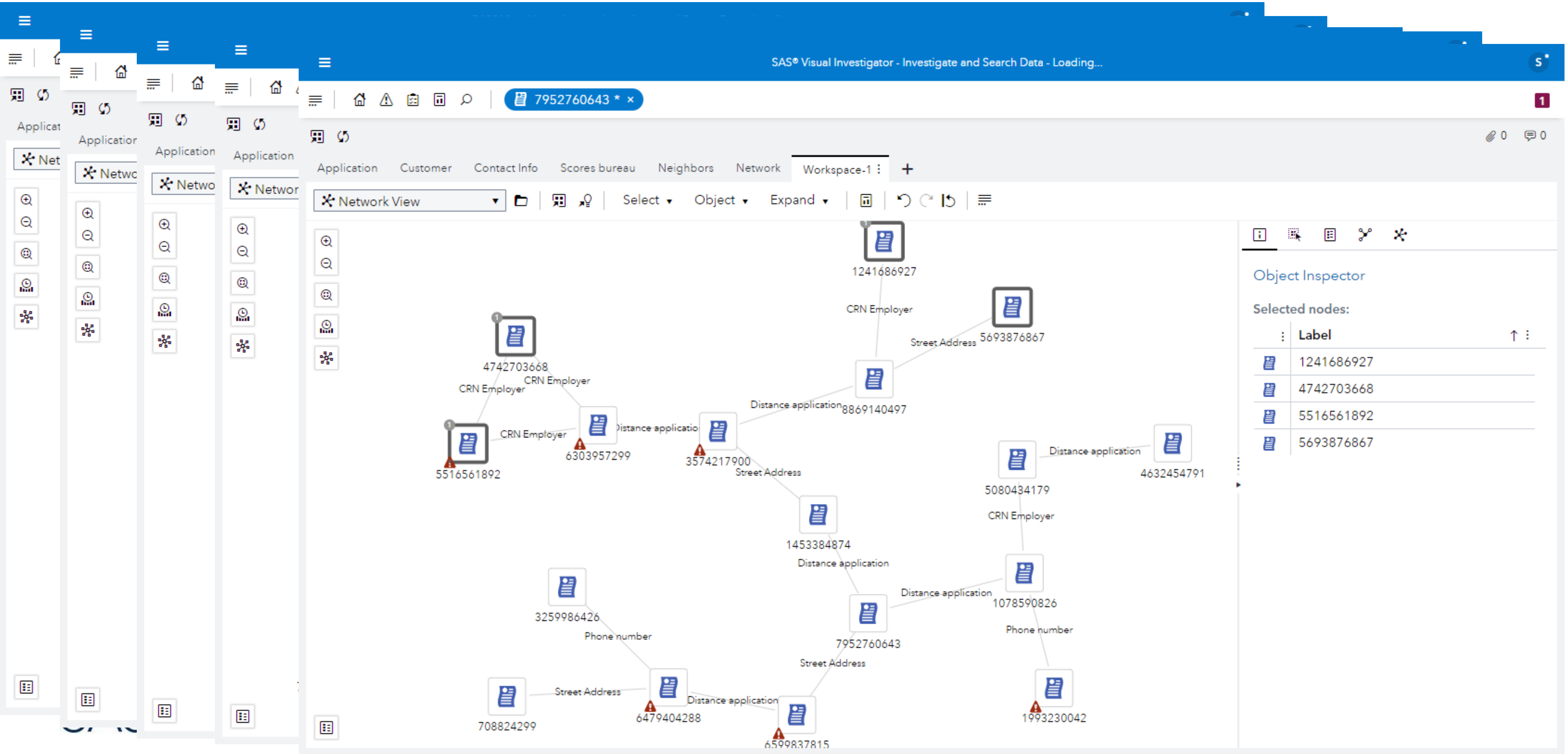
Relationship Network: a graph to understand the relationships



ERNC = 0,333

ERNC = 0,472

ERNC = 0,423

ERNC = 0,402

Thank you

Contact Information

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