

# AdvAna *and the* Guru



*The future's so  
bright I gotta  
wear shades*

Presented by CLANCY BIRRELL  
*Advanced Analytics Manager, Office of Planning Services*

# Path

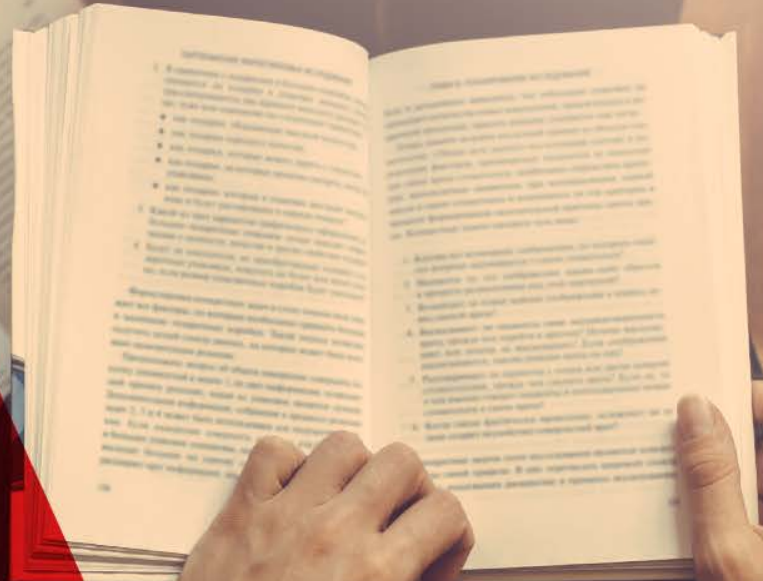
*GoT*

*Focus*

*Projects*

*Shades*

# Glossary of terms



# AdvAna – ADVanced ANALytics



*Descriptive:*

Just the facts



*Predictive:*

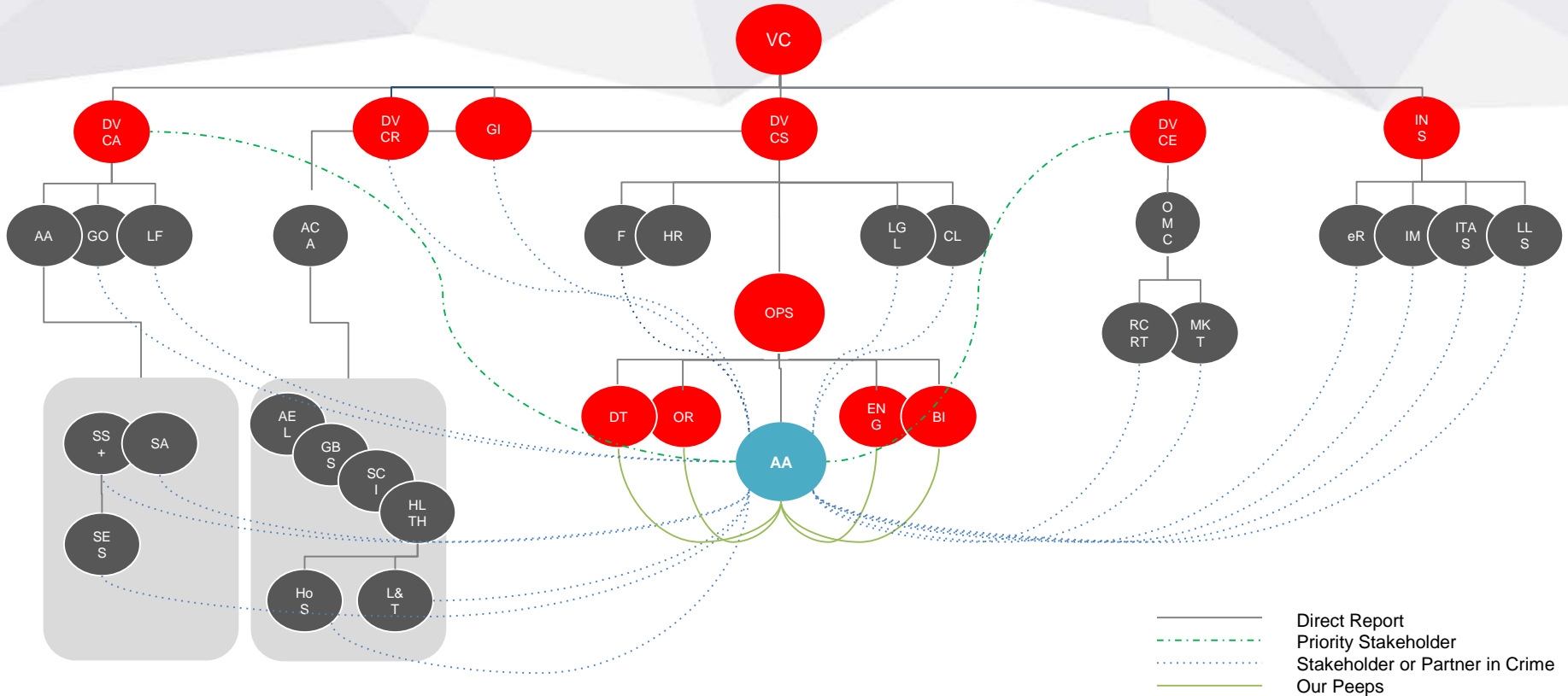
Predict the future  
based on the past



*Prescriptive:*

What happens if I push  
this shiny red button?

# The world according to...



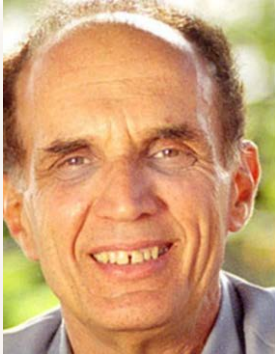
# A word on Guru's

**The gurus I have met personally, as well as those whose careers and teachings I have studied at a distance, range from crooks who could be quickly dismissed to teachers who were brilliant but flawed, to those who, while still human, seemed to possess so much compassion and clarity of mind that they were nearly flawless ...**

Sam Harris: Waking Up



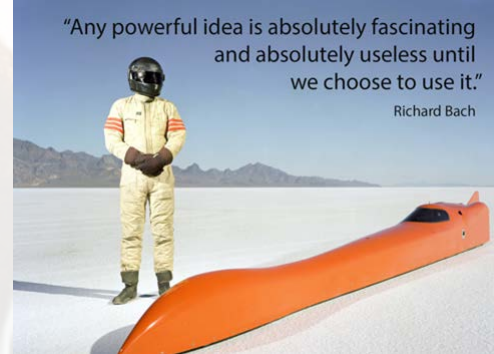
# Therefore ~



Those who ignore Statistics are  
condemned to reinvent it.

— Bradley Efron —

AZ QUOTES



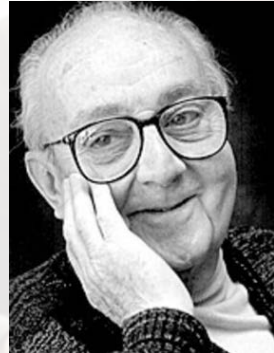
“Any powerful idea is absolutely fascinating  
and absolutely useless until  
we choose to use it.”

Richard Bach



“Without data  
you’re just  
another person  
with an opinion.”

- W. Edwards Deming,  
Data Scientist



All models are wrong, but some are  
useful.

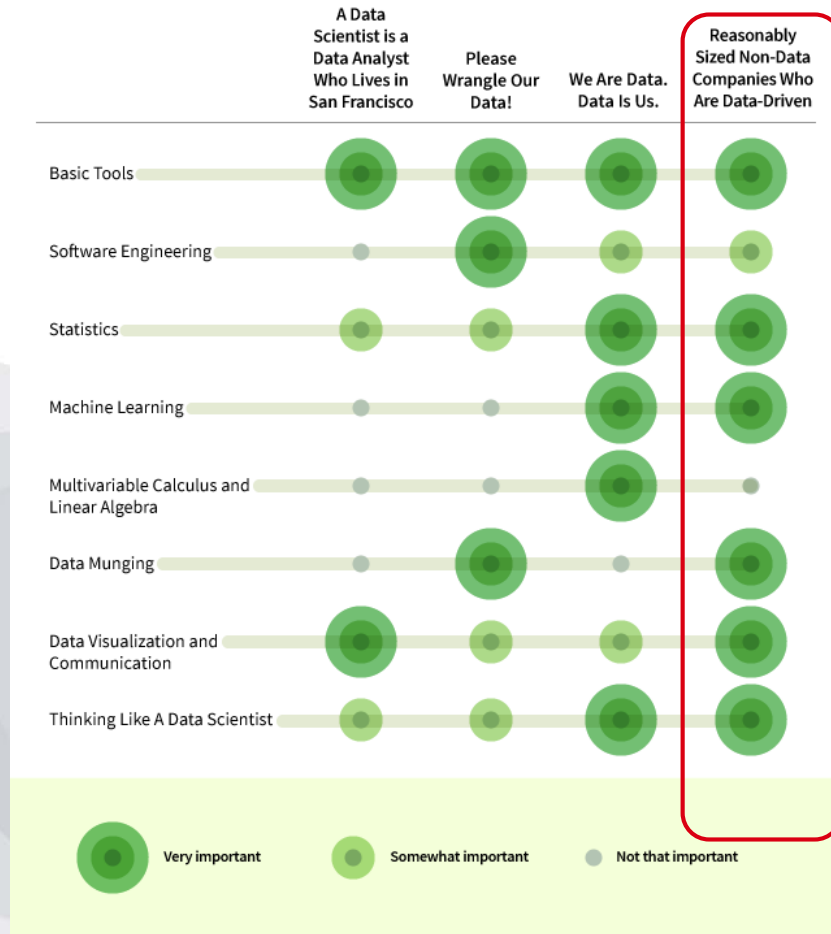
— George E. P. Box —

AZ QUOTES

# Applied statistics vs. data science



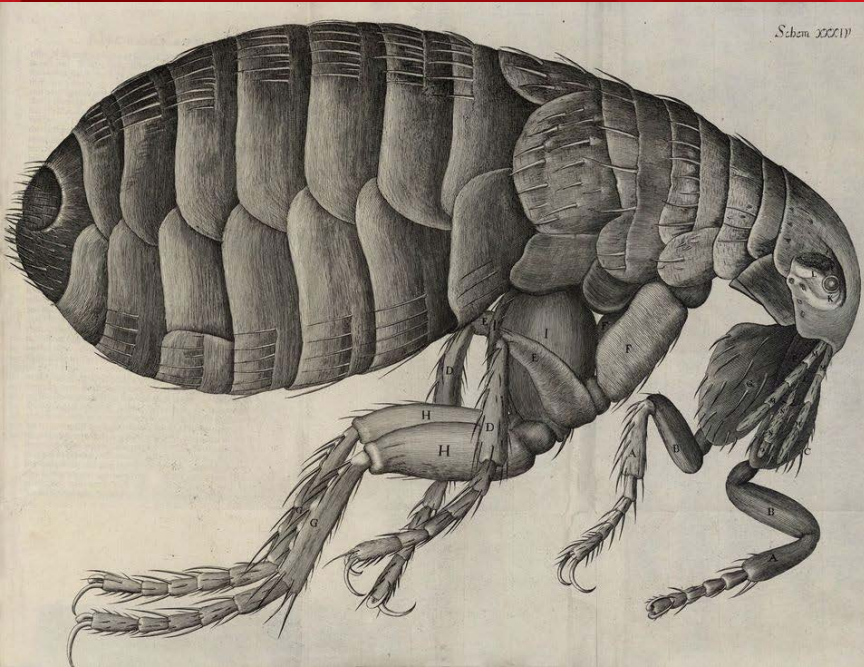




# Applied statistics vs. data science

- Standard practice
- Accepted methods
- Pre built data
- Groomed data
- Simple data sources
- Pre built point and click tools
- Running fixed and well designed experiments
- Statistical inference
- German Engineering Style Rigour
- Long form reporting of results
- Usually single domain application
- Develop statistical analyses
- No standards
- Anything that works
- Data munging
- Messy all types of data
- Many sources
- Code slinging & data carpentry
- Experimenting any which way you can
- Some statistical inference but more focus on ROI and business results
- As required rigour
- Short form results, business style strategic summaries and agile results
- Cross domain
- Develop data products

# Aaargh parasites!



- We don't exist without data!
- Low quality data = low quality analytics
- Limited access to data = limited analytics
- If the data don't exist we don't analyse it

*But above all ~*

*It all starts with a well formulated  
question.*





# Student lifecycle



Recruitment



Application



Enrolment



1st Year



2nd Year



Argh Year



Completion



Continuation



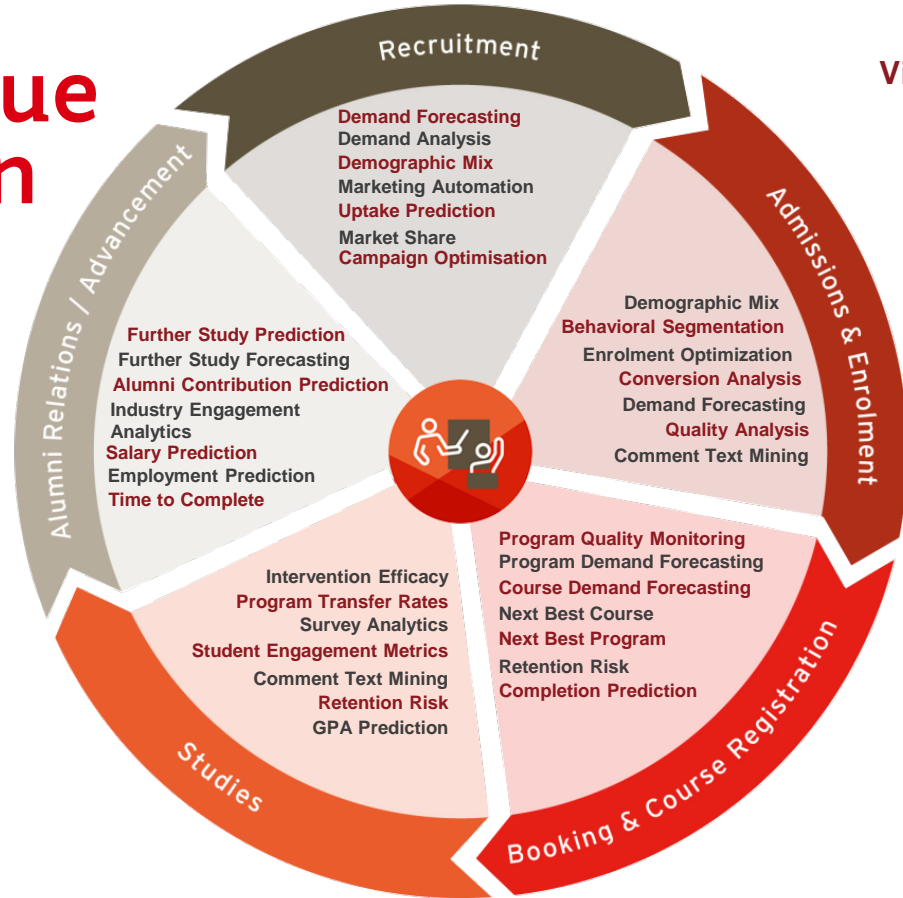
Employment

# Student Lifetime Value Optimisation

Promotability  
Staff Retention Prediction  
HR Analytics



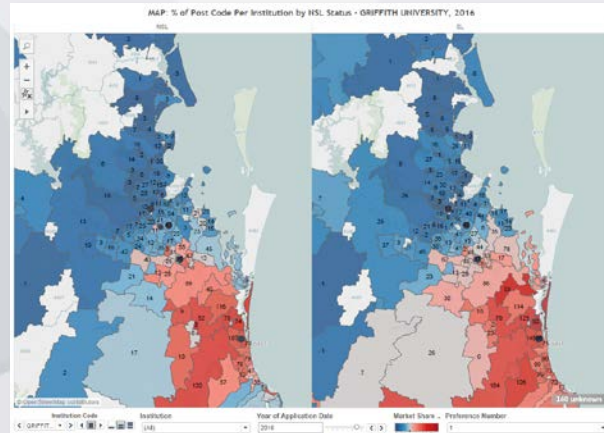
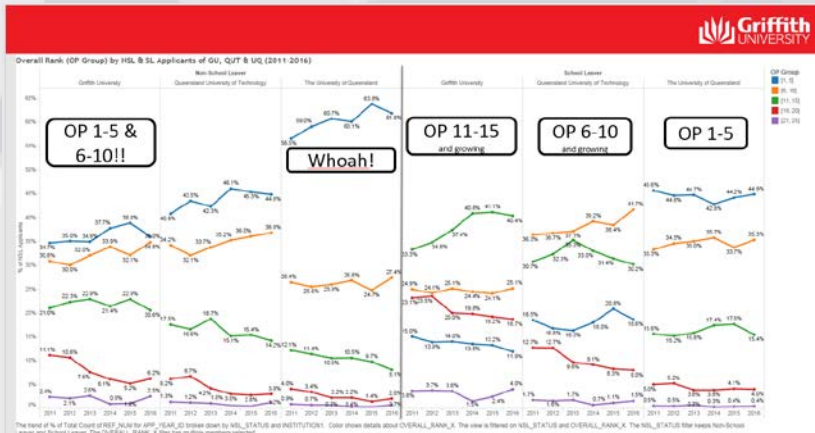
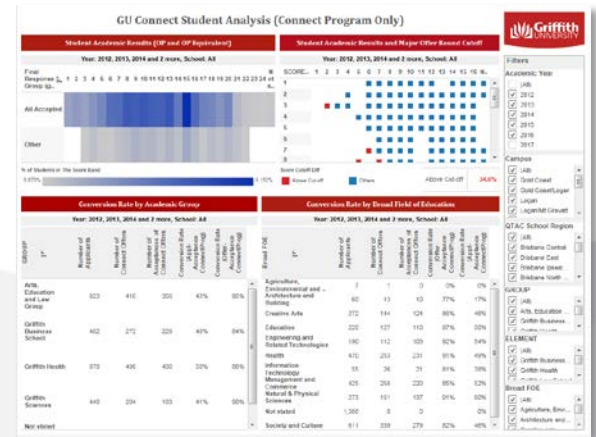
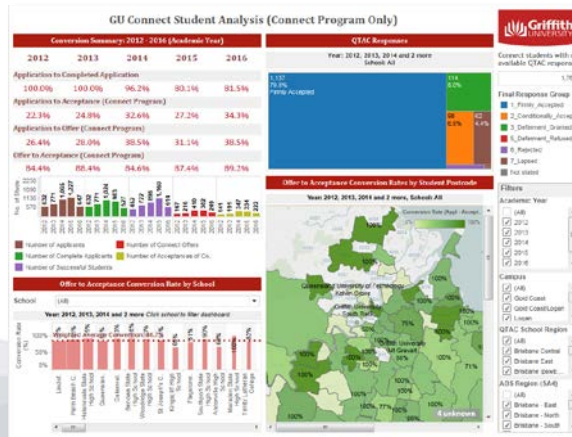
Funding Sensitivity Analysis  
Enterprise Retention Risk  
Research Project Expected Cost



Analytics Server  
Enterprise  
Visual Analysis Tool  
Student 360°  
Data Lake

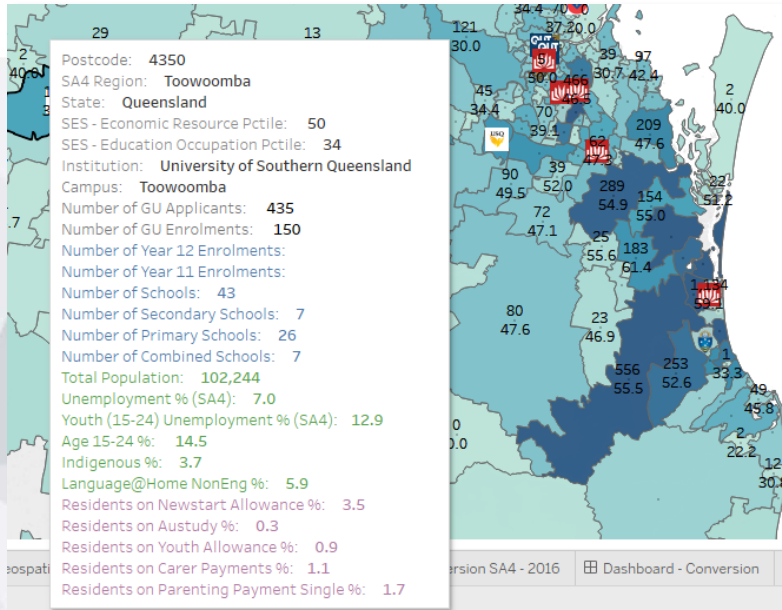


# Recruitment



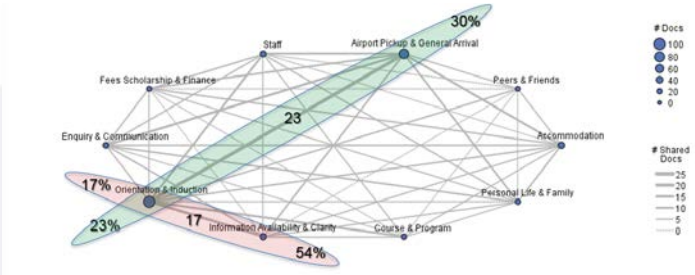


# Application + Enrolment

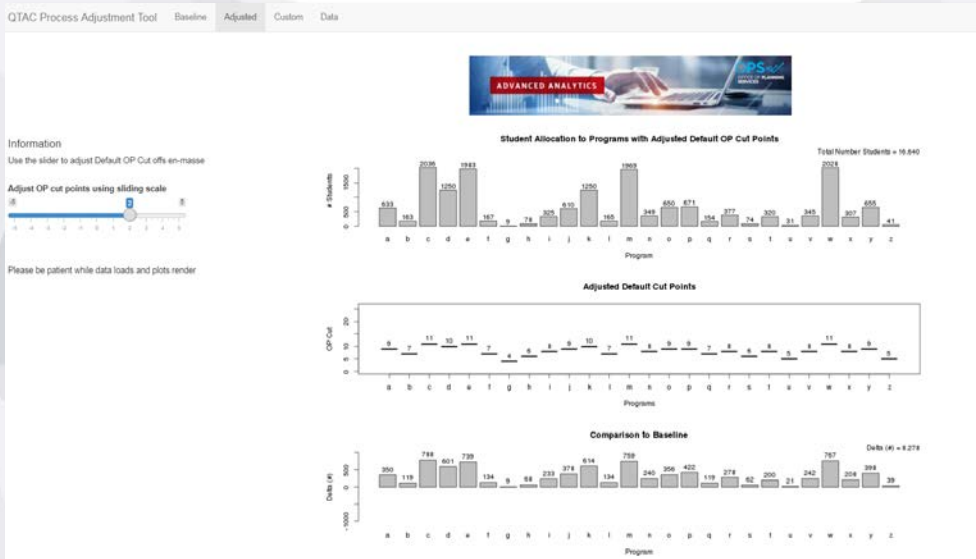
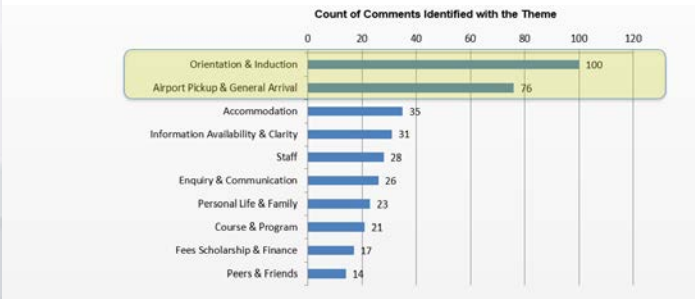


# Application + Enrolment

## Category Web (Co-occurrence of Themes)

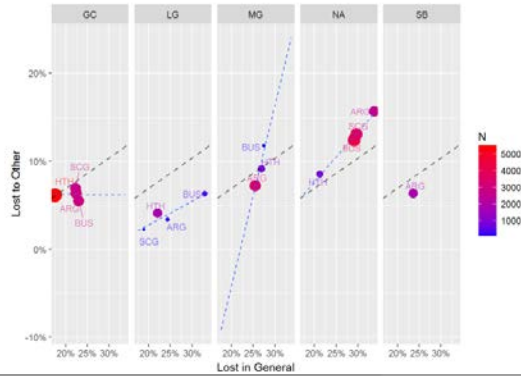


## Top 10 Key Themes



# During studies

Q: What is the relationship between general loss of students vs lost to another institution?



Prefer QUT

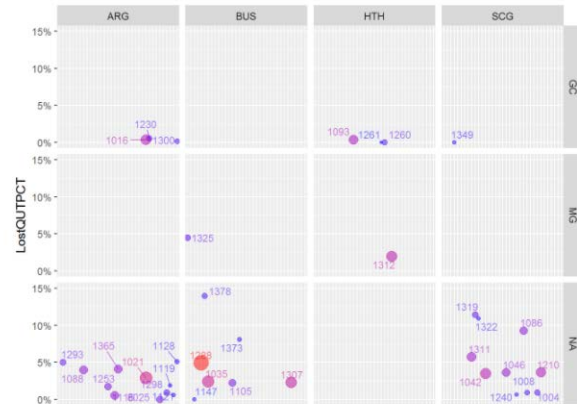
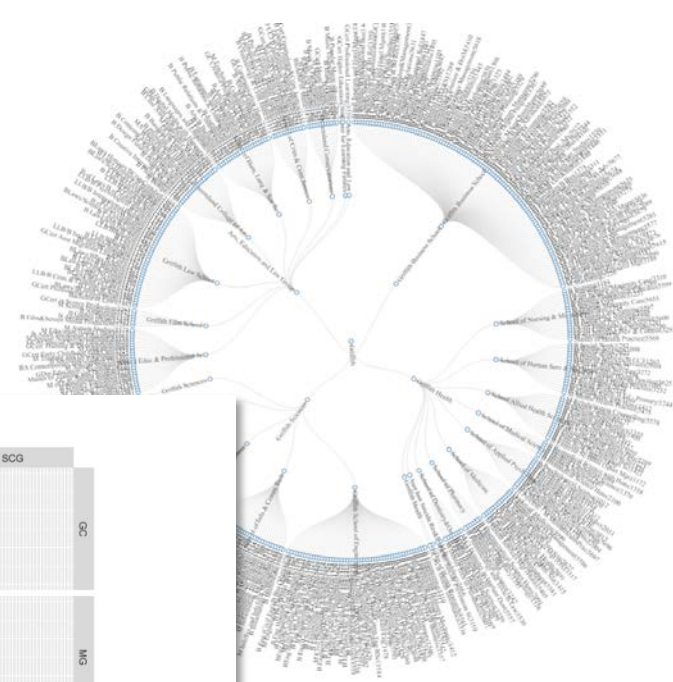
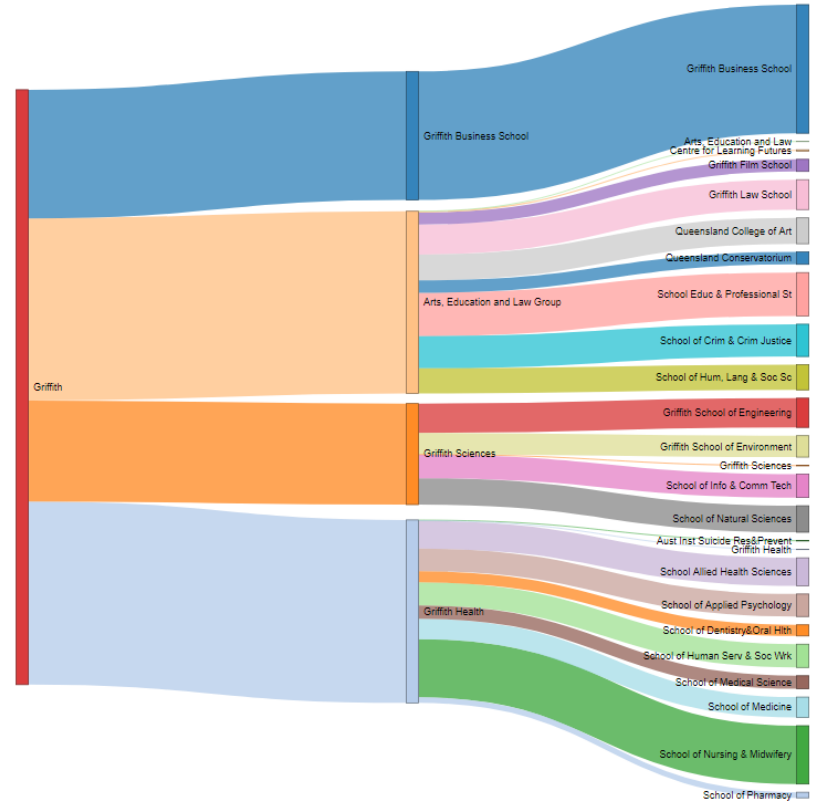
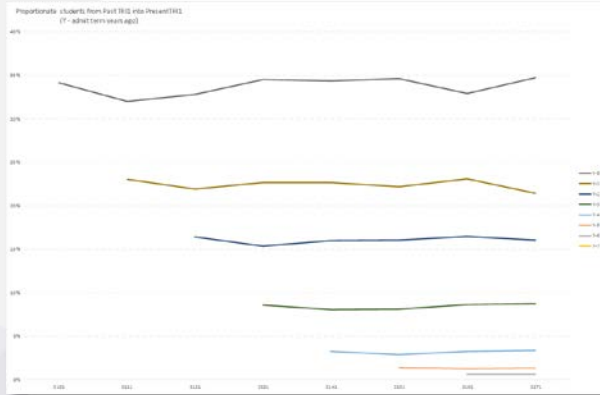
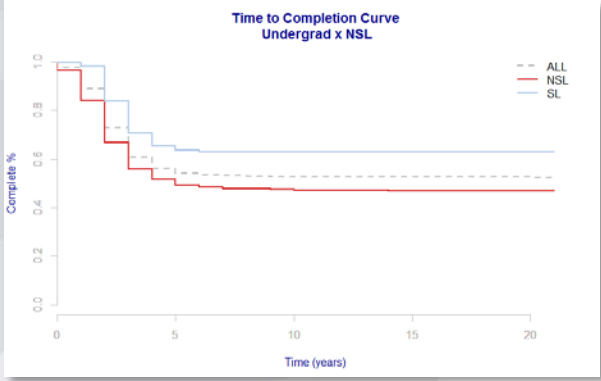


Figure 10.

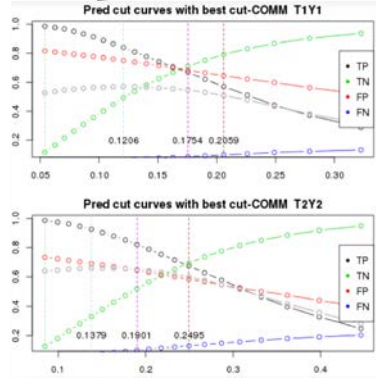
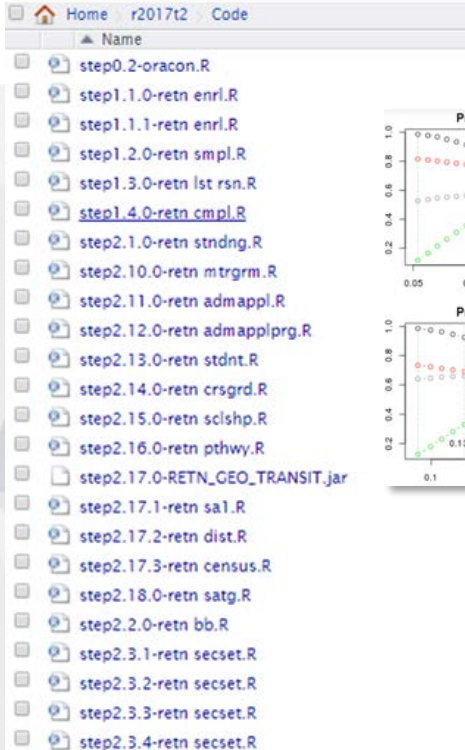
- BUS program 1378 - B Business/B Communication at Nathan campus has the highest rate of lost to QUT but is small in size
- SCG at Nathan campus seem to reflect a higher rate of lost with QUT preferences than other groups or campuses



# During studies

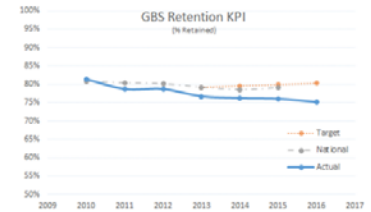


# Retention



## Bachelor Degree Retention

The proportion of all non-graduating bachelor degree students enrolled at census date in trimester one of a year (base year) who are enrolled in any Griffith program at the census date in trimester one of the next year.



Target:

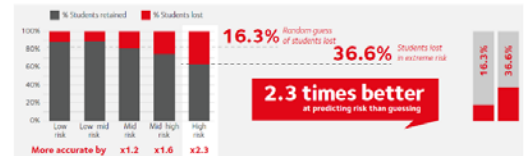
To exceed the national average for student retention by 2017

## Predictive Analytics Models

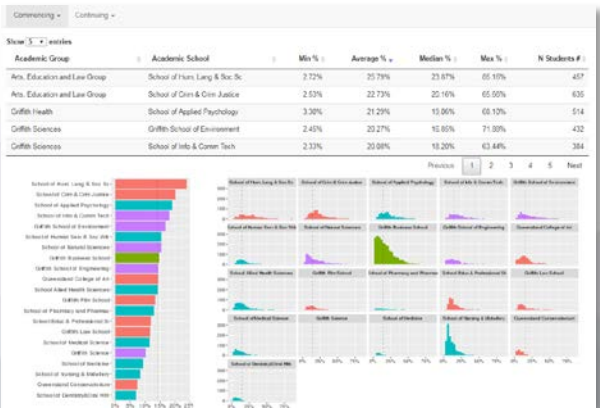
Predict Retention Risk

Machine Learning

- ✓ 1000 variables considered
- ✓ Balances True Positive & False Positives
- ✓ Identifies patterns in noisy data
- ✓ Sensitive to low volume signals
- ✓ Available NOW



# Retention

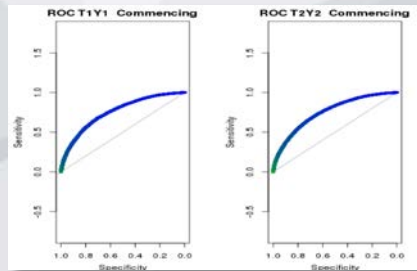


```

R File Edit Code View Plots Session Build Debug Profile Tools Help
Go to file/function Addins
4.0-runALL.R 1.2.2-gimnet d.R 3.0-organize output COMM.R
Source on Save Run Source
1 if(!require(glmnet)){install.packages('glmnet')};require(glmnet)
2 if(!require(doMC)){install.packages('doMC')};require(doMC)
3 registerDoMC(cores=15)
4
5 #####
6 ## Build mods
7
8 s <- Sys.time()
9 modCOMM1 <- cv.glmnet(y=yCOMM1,x = mmCOMM, alpha=1,family='binomial',parallel=T, nfolds=30,type.measure='auc')
10 ModelMetrics::auc(yCOMM1, predict(modCOMM1, mmCOMM, type='response',s='lambda.1se'))
11 Sys.time() - s
12
13 s <- Sys.time()
14 modCOMM2 <- cv.glmnet(y=yCOMM2,x = mmCOMM, alpha=1,family='binomial',parallel=T, nfolds=30,type.measure='auc')
15 ModelMetrics::auc(yCOMM2, predict(modCOMM2, mmCOMM, type='response',s='lambda.1se'))
16 Sys.time() - s
17
18 ###
19 # get preds
20 ptest1 <- predict(modCOMM1,mmCOMM,type='response',s='lambda.1se')
21 ptest2 <- predict(modCOMM2,mmCOMM,type='response',s='lambda.1se')
22
23 (p_actual = prop.table(table(yCOMM1)))[2])
24 actual <- yCOMM1
25 results <- data.frame('actual'=actual, 'pred'=ptest1, 'pred_class' = ptest1>p_actual)
26 names(results) <- c('actual','pred','pred_class')
27 table(results[,1], results[,3])
28
29 ## View ROCs
30 source('./Modelling/UGRD/ROCPLLOTTER.R')
31
32 par(mfrow=c(1,2))
33 ROCPLLOTTER(yCOMM1, ptest1, 'ROC T1Y1 Commencing')
34 ROCPLLOTTER(yCOMM2, ptest2, 'ROC T2Y2 Commencing')
35 par(mfrow=c(1,1))
36 dev.copy(png,paste0('./Modelling/UGRD/FitMetrics/COMM_rocplot_',Sys.Date()),'.png')
37 dev.off();dev.new()
38
  
```

ArtificialIntelligenceWork2.xlsx

M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z
AcadID	probability	category	homework	academic_group	academic_group	academic_group	academic_group	academic_group	academic_group	academic_group	academic_group	academic_group	academic_group
0.88777388	High	FALSE	Math	Math	Math	Math	Math	Math	Math	Math	Math	Math	Math
0.55457378	High	FALSE	Math	Math	Math	Math	Math	Math	Math	Math	Math	Math	Math
0.78772489	High	FALSE	Math	Math	Math	Math	Math	Math	Math	Math	Math	Math	Math
0.78172383	High	FALSE	Math	Math	Math	Math	Math	Math	Math	Math	Math	Math	Math
0.78957383	High	FALSE	Math	Math	Math	Math	Math	Math	Math	Math	Math	Math	Math
0.65657378	High	FALSE	Math	Math	Math	Math	Math	Math	Math	Math	Math	Math	Math
0.79742376	High	FALSE	Math	Math	Math	Math	Math	Math	Math	Math	Math	Math	Math
0.74534741	High	FALSE	Math	Math	Math	Math	Math	Math	Math	Math	Math	Math	Math
0.74362312	Mid-High	FALSE	Math	Math	Math	Math	Math	Math	Math	Math	Math	Math	Math
0.74037371	Mid-High	FALSE	Math	Math	Math	Math	Math	Math	Math	Math	Math	Math	Math
0.74864386	Mid-High	FALSE	Math	Math	Math	Math	Math	Math	Math	Math	Math	Math	Math
0.73453966	Mid-High	FALSE	Math	Math	Math	Math	Math	Math	Math	Math	Math	Math	Math
0.64782379	Mid-High	FALSE	Math	Math	Math	Math	Math	Math	Math	Math	Math	Math	Math
0.74377371	Mid-High	FALSE	Math	Math	Math	Math	Math	Math	Math	Math	Math	Math	Math
0.71777371	Mid-High	FALSE	Math	Math	Math	Math	Math	Math	Math	Math	Math	Math	Math
0.72037371	Mid-High	FALSE	Math	Math	Math	Math	Math	Math	Math	Math	Math	Math	Math
0.71897371	Mid-High	FALSE	Math	Math	Math	Math	Math	Math	Math	Math	Math	Math	Math
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0.69712411	Mid-High	FALSE	Math	Math	Math	Math	Math	Math	Math	Math	Math	Math	Math
0.62682378	Mid-High	FALSE	Math	Math	Math	Math	Math	Math	Math	Math	Math	Math	Math
0.64582378	Mid-High	FALSE	Math	Math	Math	Math	Math	Math	Math	Math	Math	Math	Math
0.68862378	Mid-High	FALSE	Math	Math	Math	Math	Math	Math	Math	Math	Math	Math	Math
0.70720044	Mid-High	FALSE	Math	Math	Math	Math	Math	Math	Math	Math	Math	Math	Math
0.72142378	Mid-High	FALSE	Math	Math	Math	Math	Math	Math	Math	Math	Math	Math	Math



# Analytics server



*...about those  
shades*





# Employability

## Possibilities:

- Statistical Learning
- Machine Learning Predictions
- Cluster Segmentation
- Support operational intervention testing

## What is it?

Measured by Employability Rate

Graduate Outcome Survey

4 Months from Graduation Date

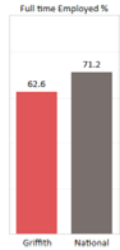
Factors

- 1) Graduates who are full time employed
- 2) Graduates who are available to be full time employed

Under the assumption:

comparative measure that represents graduate *population* Employability Rate

$$\frac{\text{Number of graduates In Full Time Employment}}{\text{Number of graduates in Available for Full Time Employment}}$$



## Levers

Results are influenced by a few things, some of which are

Population Employability Rates differ per FoE, and

Griffith FoE mix is different for both

- 1) Responders
- 2) Full Time Employed

These two things are not equal and have different impacts

Employment rate in QLD, Brisbane & Gold Coast Vs. other states and capital cities

Work readiness of our graduates



# Enterprise data visualisation

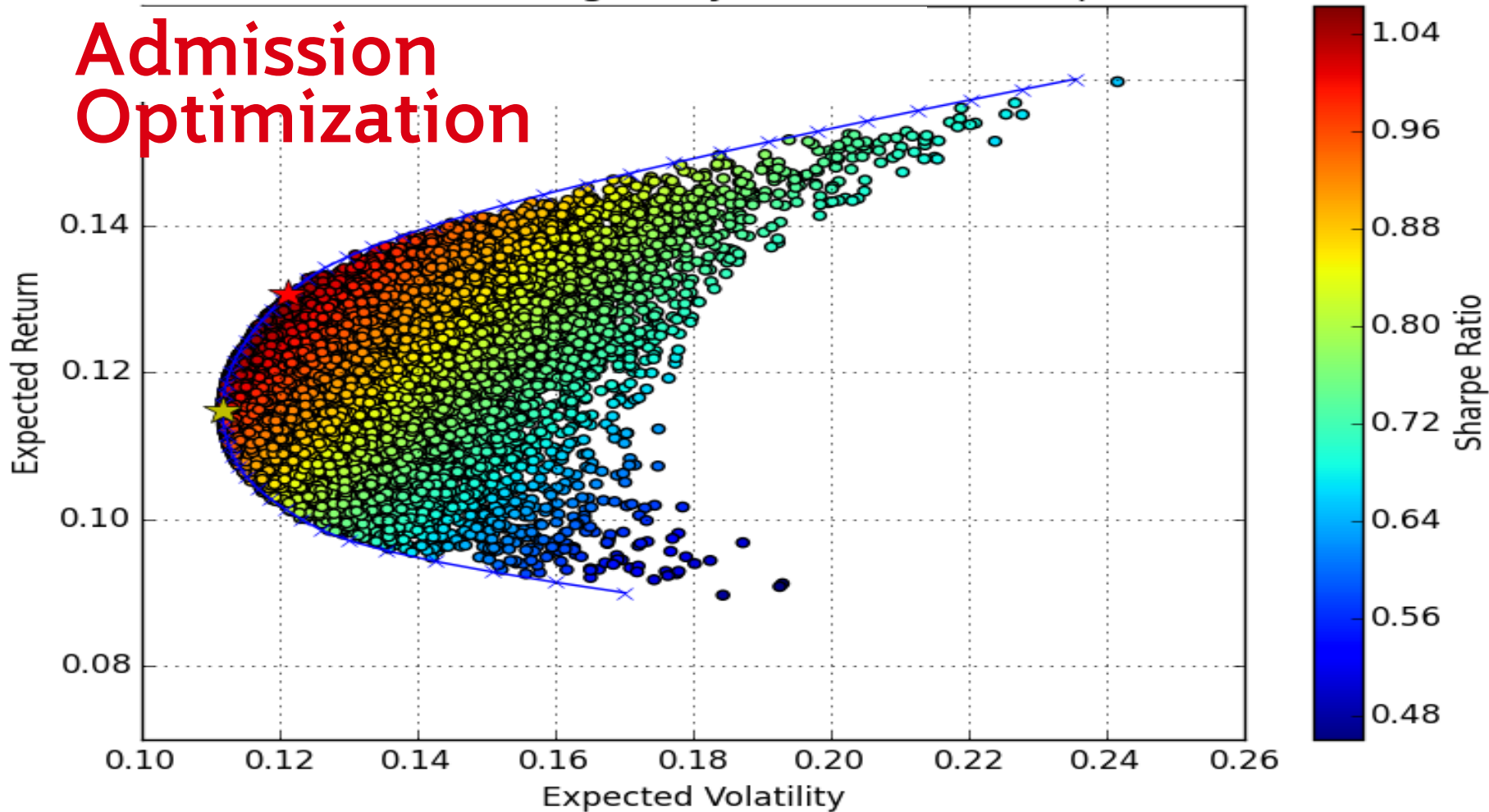
**There'll be no one to  
stop us this time.**

# Data Lake

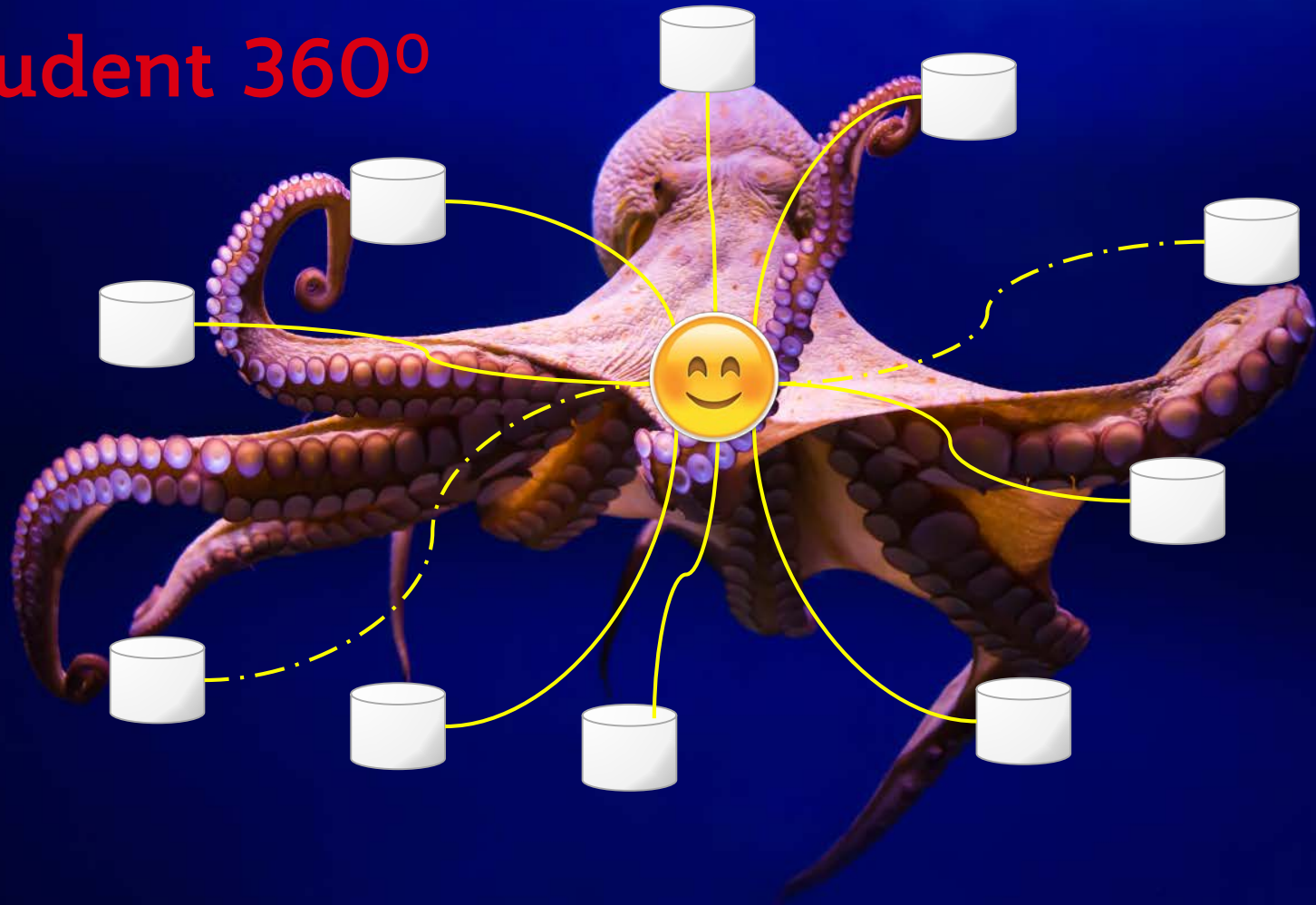


Portfolios of Google, Toyota, Coke, and Pepsi

# Admission Optimization



# Student 360°



# Success measures

GPA prediction

PGRD Conversion Probability

RSCH Conversion Probability

Research Success Predictions:

- Publications,
- Time to Complete,
- Grant \$'s

# Finance

Student Lifetime Value

Research Project Expected Cost

# HR Analytics

Promotability

Retention: Pre and Post Hire

Future Salary

Fraud





So much to do...

What is the path, past, present, future of analytics nirvana at Griffith

Where Clancy takes us through the hopes, tears, fears and findings from the OPS Advanced Analytics team with examples of real life products, projects and future possibilities.

Clancy is an Applied Statistician/Data Scientist. He has experience in all data analytics paradigms and extensive data mining experience. He has qualifications in mathematics, statistics, machine learning and data science.

You'll get a taste of the practical every day application of advanced analytics @ Griffith as well as some dreamy stuff that we'd like to be doing in the future.

What is Data Science, What is Descriptive, Predictive & Prescriptive Analytics?

Is deep learning or big data on our dance card?

What about AI?

What are the questions at Griffith that Analytics can help answer, the big and the not so big?

A blurred background of a business meeting. In the foreground, several people's hands are raised, indicating they want to ask a question or make a point. The people are out of focus, but their attire (suits, blouses) suggests a professional setting. The overall scene is brightly lit, possibly from large windows in the background.

QUESTIONS



# THANK YOU



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