

# *Aussie Pies*



*the great Australian bite. . .  
...coming to Toronto*

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<b>Commission:</b>	IBM Data Science – Coursera

## the big idea



- Deliver Aussie pies as an additional sales opportunity for food outlets, offering a great product with a difference.
- Agile, scalable market entry for a new venture



## the business profile



- Australian investor
- business to business distribution – not a shop front
- Toronto, Canada
- pre-start up concept



## why aussie pies



- ✓ the great Australian bite
- ✓ convenient hand sized snack
- ✓ tasty pastry bowl and lid
- ✓ delicious dollop of meat fillings
- ✓ one for a snack – two for a meal – mix and match
- ✓ fair dinkum, true blue, real deal aussie meal



## scope of analysis



- preparatory research, may form part of future business case
- create profile of Toronto metropolitan venue
- understand potential venues likely relevance

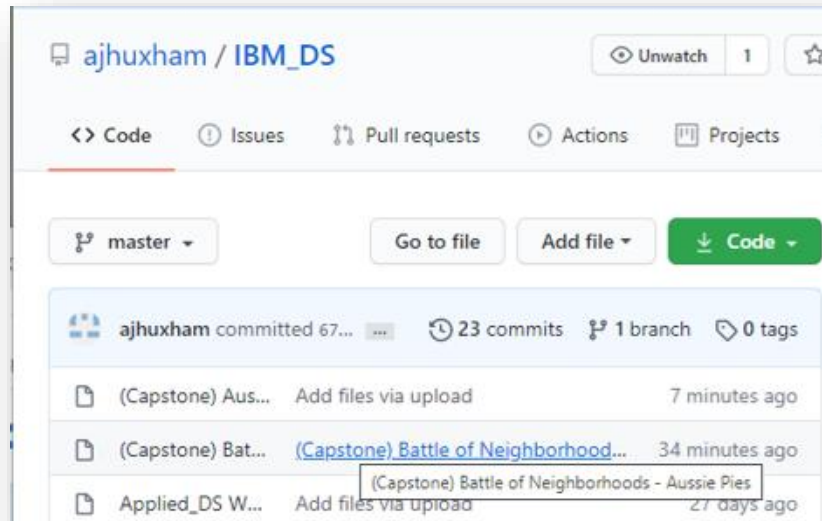
*(support, complement, challenge)*





# extra perspectives *references to follow*

- Jupyter notebook  
(code cell references at page footer)



[https://github.com/ajhuxham/IBM\\_DS/blob/master/\(Capstone\)%20Battle%20of%20Neighborhoods%20-%20Aussie%20Pies.ipynb](https://github.com/ajhuxham/IBM_DS/blob/master/(Capstone)%20Battle%20of%20Neighborhoods%20-%20Aussie%20Pies.ipynb)



- Full report



[https://github.com/ajhuxham/IBM\\_DS/blob/master/\(Capstone\)%20Aussie%20Pies%20in%20Toronto%20-%20Report.pdf](https://github.com/ajhuxham/IBM_DS/blob/master/(Capstone)%20Aussie%20Pies%20in%20Toronto%20-%20Report.pdf)

data matters  
*venue profiles*



### supporters

- Most likely add aussie pies to product line

### complementary

- adds to the overall area identity
- attracts potential customers

### challengers

- most likely not to welcome the business



data matters  
*venue groups*



### supporters

- Casual eateries
- Bars and pubs

### complementary

- Restaurants
- Specialty eateries
- Transportation
- Household supplies
- Lifestyle
- Other

### challengers

- Bakeries





# data matters

## *sources*



### target areas

- **Wikipedia:** Practical and accessible, fit for purpose
- **Postal codes:** mail delivery area for borough and neighborhoods around Toronto
- **Borough:** municipality
- **Neighborhood:** smaller community of borough

### spatial coordinates

- **Cognitive lab:** permissions needed for access
- **Coordinates:** latitude and longitude
- **Postal codes:** mail delivery areas
- **Target area:** borough, neighborhood

### venue information

- **Foursquare:** requires permissions for access
- **Venues:** name and category of venue
- **Coordinates:** latitude and longitude



data matters

*sources - overlaps*



Data type	Wikipedia - M Postal Codes - Canada	Cognitive - Geospatial Data	Foursquare	Total sources
Borough				1
Latitude				2
Longitude				2
Neighborhood				1
Postal Code				2
Venue Name				1
Venue Category				1
Total fields	3	3	4	10



# data matters *solutions*



## database

- **Database:** refined to boroughs with 'Toronto' in name
- **Constraints:** venue details limited to 100 records per 500 metre radius from neighborhood centre

## modelling

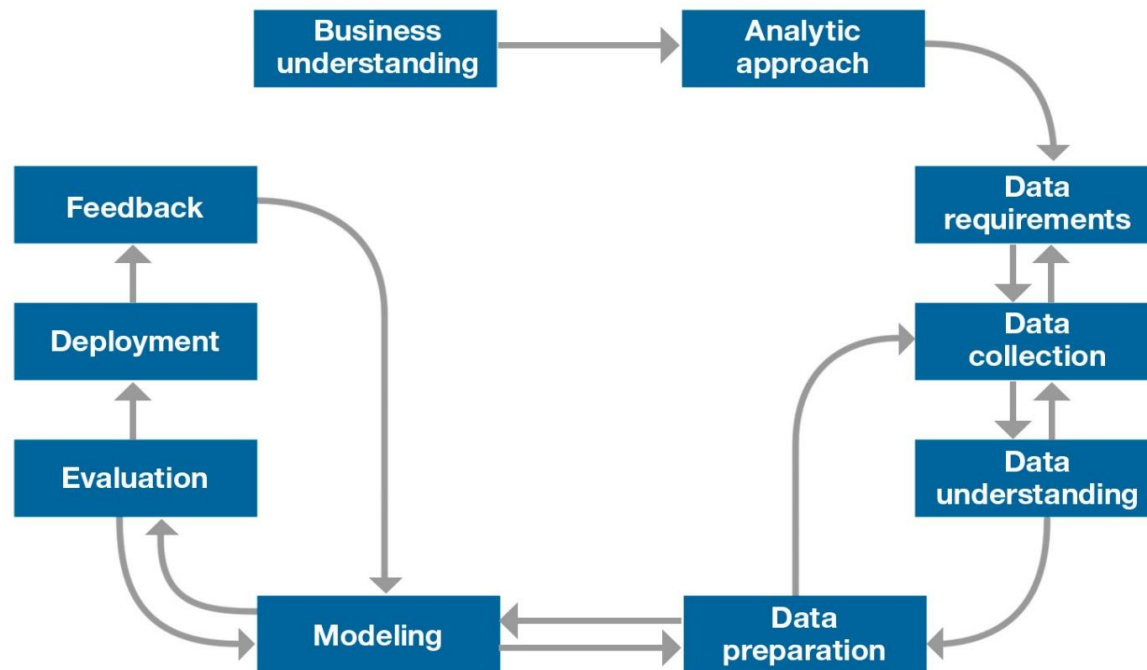
- **Classifications:** Numeric conversions of venue categories
- **Clusters:** identification of themes, clusters and outliers

## visuals

- **dataframes:** matrix (table) of venues by category, area, clusters
- **Maps:** Spatial context, category clusters



# analysis *guiding method*



[https://www.ibmbigdatahub.com/blog/why-we-need-methodology-data-science.](https://www.ibmbigdatahub.com/blog/why-we-need-methodology-data-science)



## why a method

- **Value:** repeatability, reliability of results determines value
- **Confidence:** structured, tested process to generate results

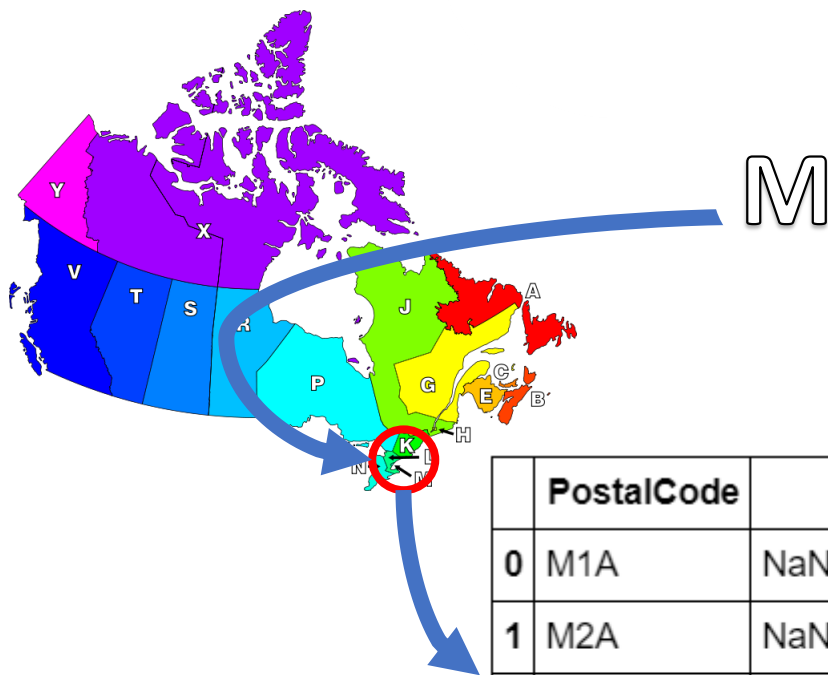




# defining target neighborhoods part 1

## *creating the first data frame*

[https://commons.wikimedia.org/wiki/File:Canadian\\_postal\\_district\\_map.svg](https://commons.wikimedia.org/wiki/File:Canadian_postal_district_map.svg)



### results

- **Source:** target areas, Canadian postal code 'M'
- **Start:** 180x rows of postal records; many records 'not assigned'
- **Preparation:** removed records 'not assigned'
- **Result:** 103x rows of boroughs and neighborhoods

	PostalCode	Borough	Neighborhood
0	M1A	NaN ❌	Not assigned ❌
1	M2A	NaN ❌	Not assigned ❌
2	M3A	North York	Parkwoods
3	M4A	North York	Victoria Village
4	M5A	Downtown Toronto	Regent Park, Harbourfront

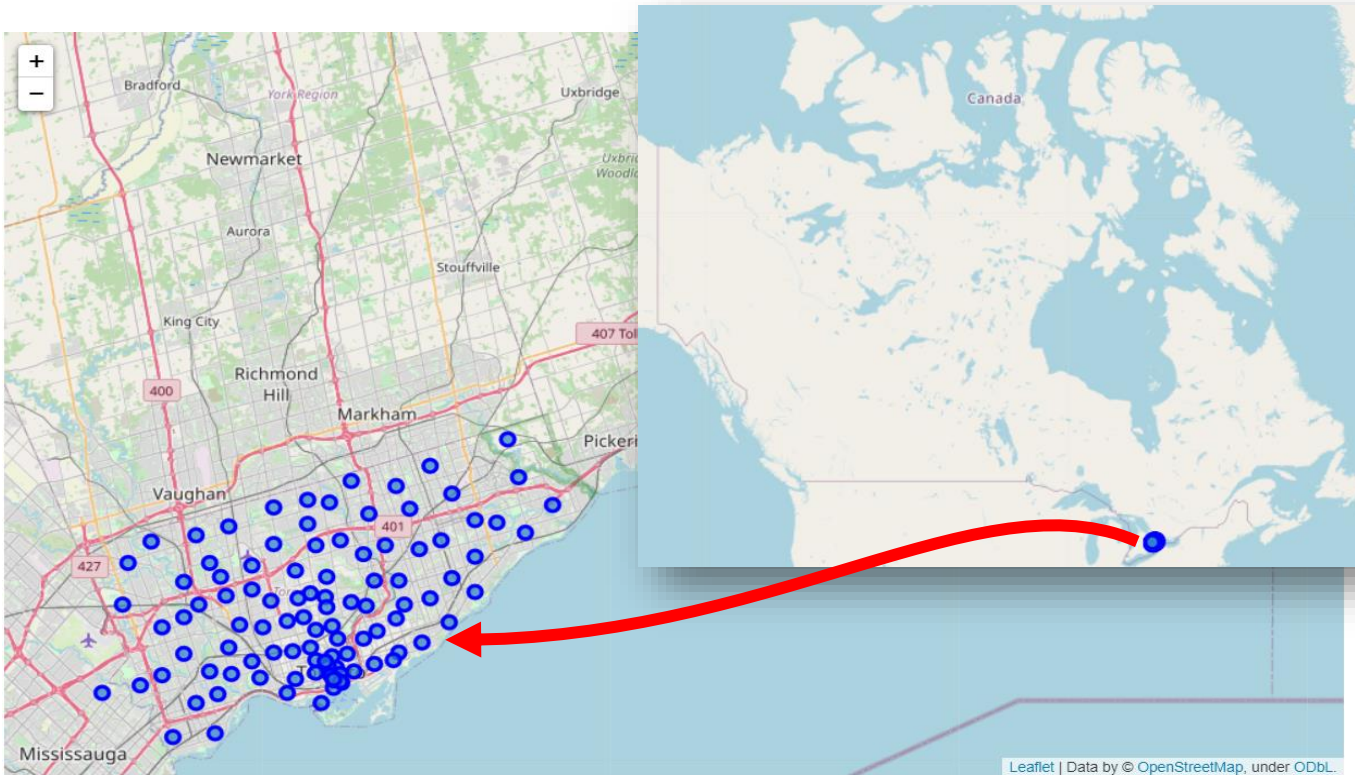


Notebook cell references: ([0] – [5])



# defining target neighborhoods part 1

## *integrating geospatial records*



## results

- **Source:** target areas dataframe + import geospatial coordinates
- **Preparation:** join dataframes on postal code; mapping algorithms
- **Result:** neighborhood centres overlaid on map of Toronto, Canada



Notebook cell references: ([6] – [10])

## defining target neighborhoods part 2

### *refining the scope + integrating venue records*



	Neighborhood	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
0	The Beaches	43.676357	-79.293031	Glen Manor Ravine	43.676821	-79.293942	
1	The Beaches	43.676357	-79.293031	The Big Carrot Natural Food Market	43.678879	-79.297734	Health Food Store
2	The Beaches	43.676357	-79.293031	Grover Pub and Grub	43.679181	-79.297215	Pub
3	The Beaches	43.676357	-79.293031	Upper Beaches	43.680563	-79.292869	Neighborhood
4	The Danforth West, Riverdale	43.679557	-79.352188	MenEssentials	43.677820	-79.351265	Cosmetics Shop

- Venue coordinates unique but very close to 'nearby' neighborhoods
- Limit 100 venues within 500 meters of neighborhood center

## results

- **Source:** target areas dataframe + import Foursquare venue records
- **Preparation:** new dataframe limited to boroughs with 'Toronto' in name; append venue name, categories on nearby spatial coordinates
- **Result:** new dataframe report of 1,614 venues across target neighborhoods



Notebook cell references: ([11] – [16])

## quantify venues by category

### *descriptive statistics*

Top 5	Count
Coffee Shop	143
Café	89
Restaurant	54
Italian Restaurant	41
Hotel	37

Venue count / category	Value
Total categories	233.000000
Maximum	143.000000
Minimum	1.000000
Mean (average)	6.927039
Standard deviation	13.058515



## results – indicating variety

- **Preparation:** group by venue category; descriptive statistics of venue category quantities
- **Result:** dataframe of venue categories (showing **sample** top 5 by count), summary statistics by count



Notebook cell references: ([17] – [19])



## modelling

### *report most common venues*

Neighborhood groups	1st Most Common Venue	10th Most Common Venue
Berczy Park	Coffee Shop	Shopping Mall
Brockton, Parkdale Village, Exhibition Place	Café	Furniture / Home Store
Business reply mail Processing Centre, South C...	Light Rail Station	Pizza Place
CN Tower, King and Spadina, Railway Lands, Har...	Airport Lounge	Airport Gate
Central Bay Street	Coffee Shop	Bubble Tea Shop



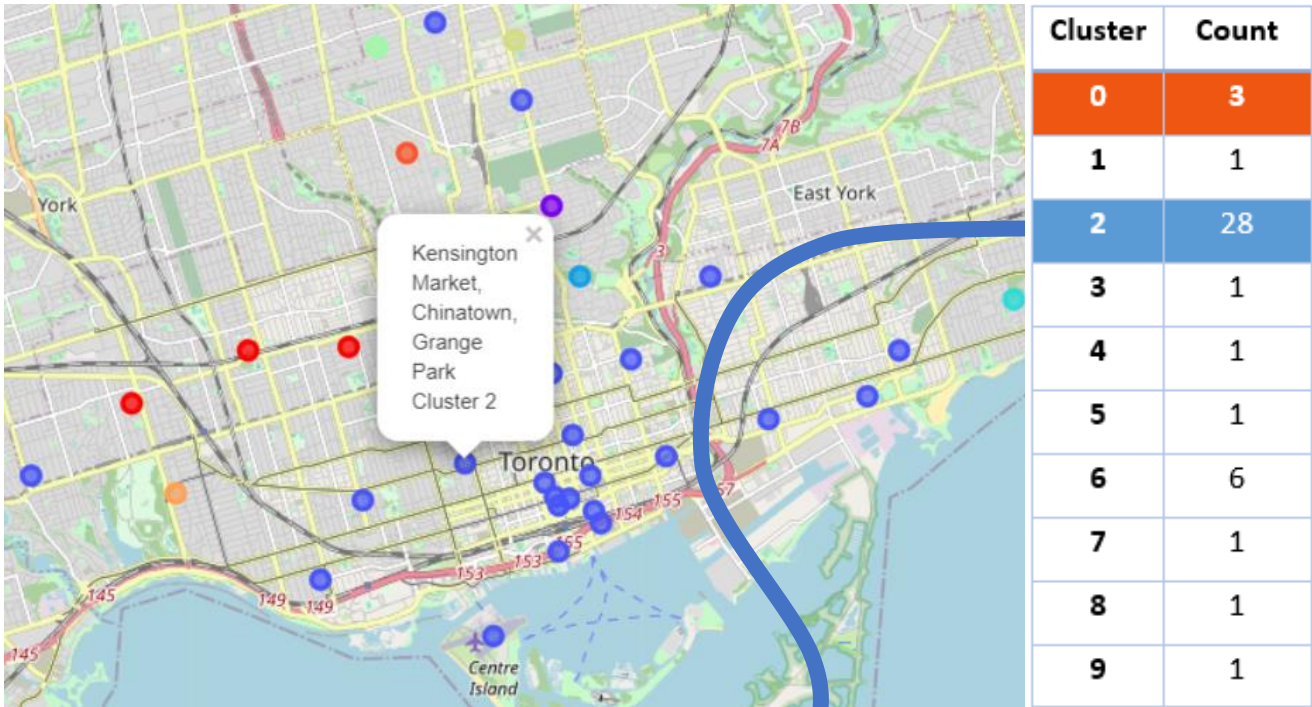
## results – common venue report

- **Preparation:** numeric transformation of category text records, groupings of venues common to neighborhoods
- **Result:** dataframe of 10 most common venue categories across neighborhoods (showing [sample](#) of top 5 groups, 1<sup>st</sup> and 10<sup>th</sup> most common)



Notebook cell references: ([20] – [24])

modelling  
*map of most common venues*



Cluster 2 sample

	Latitude	Cluster Labels	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue
41	43.679557	2	Greek Restaurant	Coffee_Shop	Italian Restaurant	Bookstore	Ice Cream Shop
42	43.668999	2	Sandwich Place	Park	Fast Food Restaurant	Pizza Place	Gym



results – venue clusters

- **Preparation:** Kmeans cluster algorithm generating 10x clusters (0-9), assigned colours + mapping
- **Result:** 10x cluster groups overlaying metro Toronto, dominated by cluster 2 (blue)





grouping by most common venues  
*map of most common venues*  
*+ clusters*



## results – venue clusters

- **Preparation:** Venue categories manually allocated a group using a spreadsheet
- **Result:** report defining the profiles as per the business requirement

Group	Quantity	% of total Quantity
Restaurant	406	25.11%
Casual eatery	307	18.99%
Lifestyle	248	15.34%
Specialty eatery	237	14.66%
General retail	220	13.61%
Bar / Pub	82	5.07%
Bakery	41	2.54%
Hotel	37	2.29%
Transport	21	1.30%
Other	15	1.11%
Total	1614	

- *Prospective Supporters: Casual eateries 2<sup>nd</sup> largest group + Bar / Pubs*
- *Prospective Challengers: Bakeries ~<2.6%*



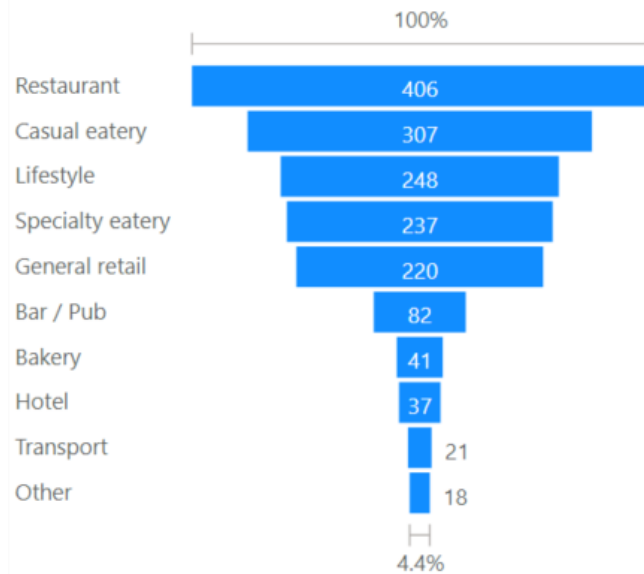
**Note: performed separately on a spreadsheet**

# grouping venue categories

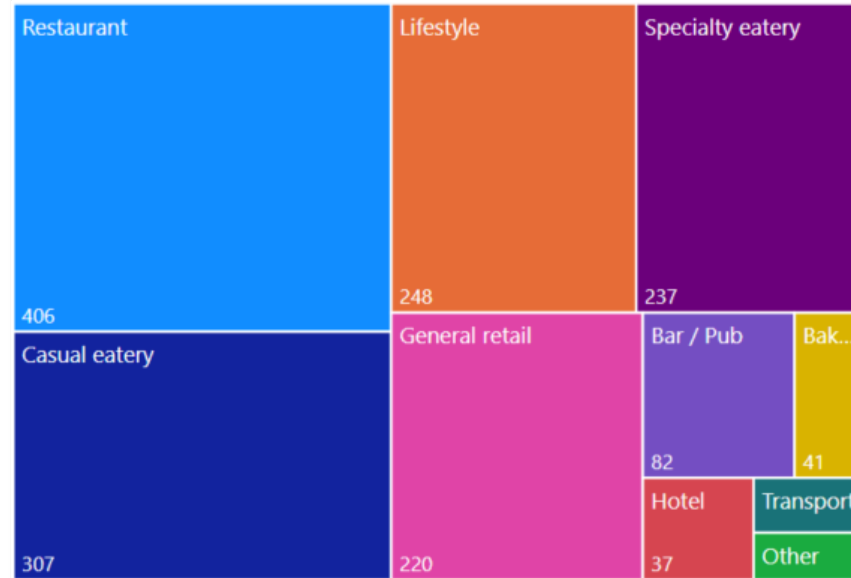
## *venue group profiles*



‘Funnel chart’



‘Tree map’



## results – group

- **Preparation:** Microsoft PowerBi used the Python data to create visuals
- **Result:** visuals showing comparative groups sizes across target neighborhoods

same information – shown different ways



Note: produced using Microsoft Power PI

## grouping venue categories *international food themes*

Nationality	Quantity
Japan	59
Italy	41
United States	39
Thailand	30
Mexico	22
France	21
Greece	17
China	11
Saudi Arabia	8
Brazil	7
India	7
Total	255



No great  
Australian  
Bites!



### results – national foods

- **Preparation:** Grouped foods by nationality represented
- **Result:** visual indicating spread of national foods represented, with proportionate circle markers





# analysis – quick review

## *additional analysis*

How methodology was applied  
though out the analysis steps



Methodology Step	Defining the Target Neighborhoods - part 1	Defining the Target Neighborhoods - part 2	Grouping venue categories by data priority	Modelling	Quantify venues by category	Grand Total
Step 1 - Business understanding	1					1
Step 2 - Analytic approach	1					1
Step 3 - Data requirements	1					1
Step 4 - Data collection	2	1				3
Step 5 - Data understanding	2	2	2		1	7
Step 6 - Data preparation	1	Data preparation was continuous, requires most of the work				8
Step 7 - Modelling				2		2
Step 8 - Evaluation				1		3
Grand Total	9	5	3	7	2	26

Steps 9 and 10 pending acceptance  
to progress by the business sponsor



analysis – quick review  
*additional analysis*



## suggestions for potential future analysis

- **refine clusters:** the cluster sets can continue to be refined, perhaps narrowing the areas of interest for this embryonic business proposal
- **demographics:** integrating socio-economic demographics with the venue categories may enhance the profile to understand potential customer base

## the analysis mandate

- **status:** an initial profile of venue groups in metropolitan Toronto has been created
- **evaluate mandate:** the business sponsor needs to confirm if further analysis is warranted – no point if the decision is not to progress





## conclusion *basic metrics*



- **Target neighborhoods:** A shortlisted focal subset of **39** boroughs that include 'Toronto' in the name was systematically refined from an initial list of **180** postal codes.
- **Data priority:** The venue categories were grouped according to the data priorities, reshaping the perspective to show restaurants as the most prominent venue across the sample set.
- **Venue diversity:** The **1,617** venues across **233** unique categories identified, with coffee shops and café's as the most prominent.



## conclusion *indications*



- **Opportunity:** Australian pies appear to be a relatively distinct product opportunity
- **Next steps:** reasonable prospects to 'have a go'



## conclusion *themes*



- **Venue clusters:** The clusters of most common venues per neighborhood are represented by dataframe reports and street maps overlaid with markers indicating the clusters.
- **Venue grouping profile:** Approximately 24% of the 1,614 identified venues are either casual eateries or bar/ pubs, fitting the prospective market as potential distributors. Less than 3% are bakeries selling pastry products.
- **National food themes:** Venue categories indicate a diverse representation of international cuisines, of which Japan, Italy and United States dominate.

*Australia in general and Australian pies in particular do not appear represented.*

