Marketing Analytics

Lecture 4 Transaction Analytics (II)

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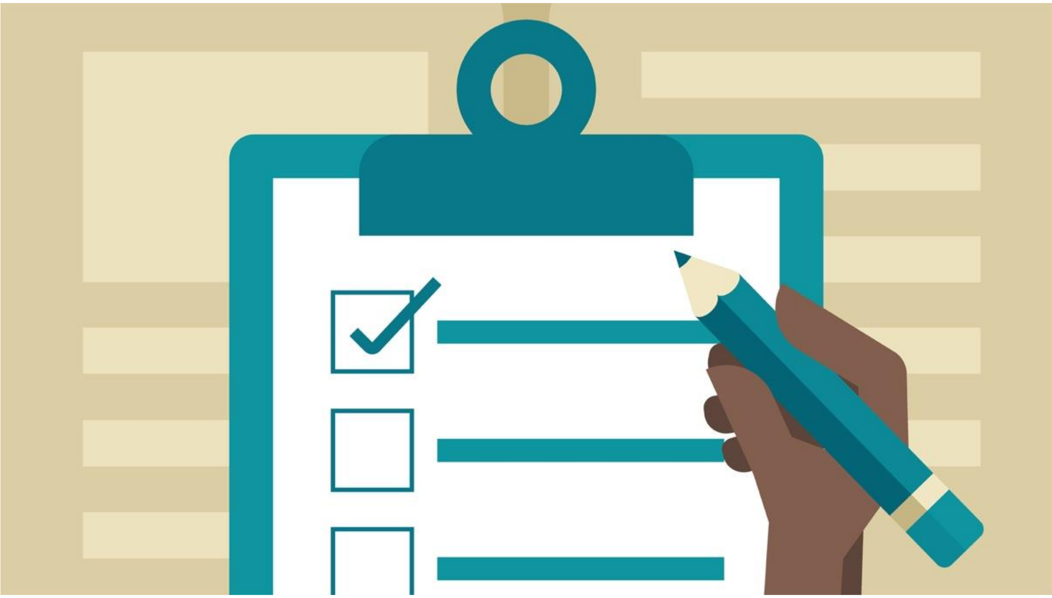
What we introduced last week..

- Transaction Data
- Analysis Levels: Individuals & Aggregation
- Segmentation

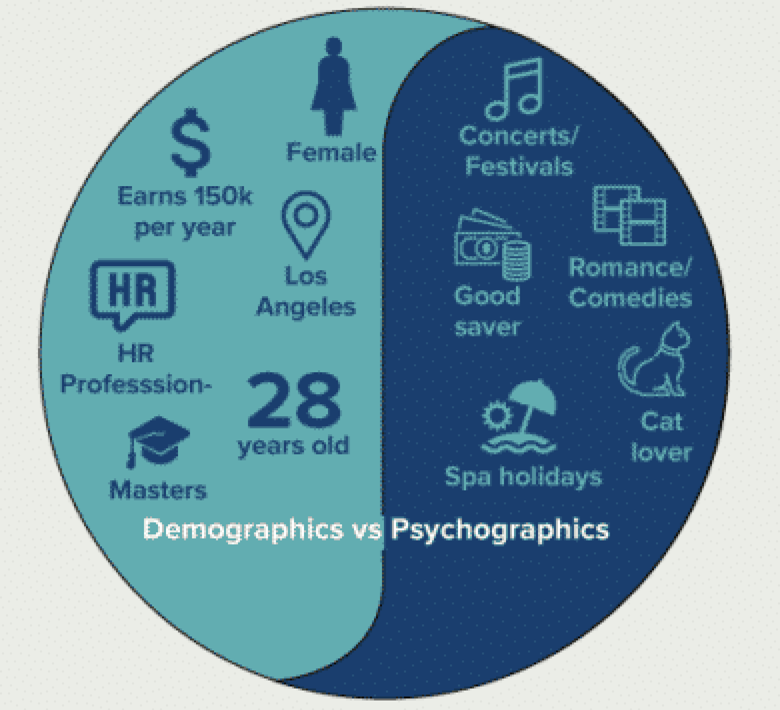
Learning Objectives

- Understand how to assess and characterize purchase dynamics
- Know how to perform relevant analysis and interpret the results



Segmentation (Continued)

- Segmentation is a marketing strategy aimed at dividing the market into sub-markets, wherein each member in each segment is very similar by some measure to each other and very dissimilar to members in all other segments.



- Demographic segmentation: age, gender, income, education, marital status, and occupation
- Psychographic segmentation: lifestyle, personality traits, values, and attitudes

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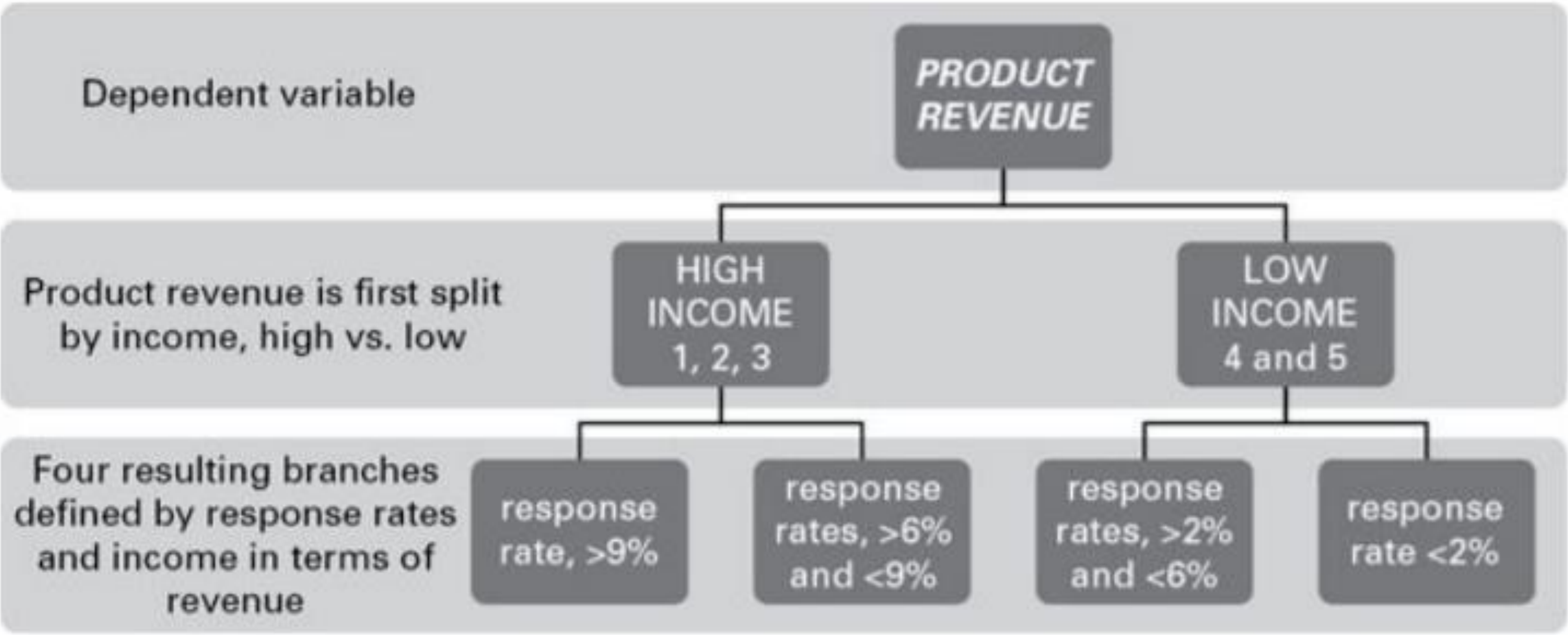
Segmentation – Chi-squared Automatic Interaction Detection (CHAID)



- ❖ Dependent-variable (DV) approach
- ❖ Dependent variable is product revenue
- ❖ The best split is found to be income
- ❖ The next best variable is response

- ❖ Easy to use, easy to explain
- ❖ But it is heuristic, no coefficients, no signs (positive/negative)

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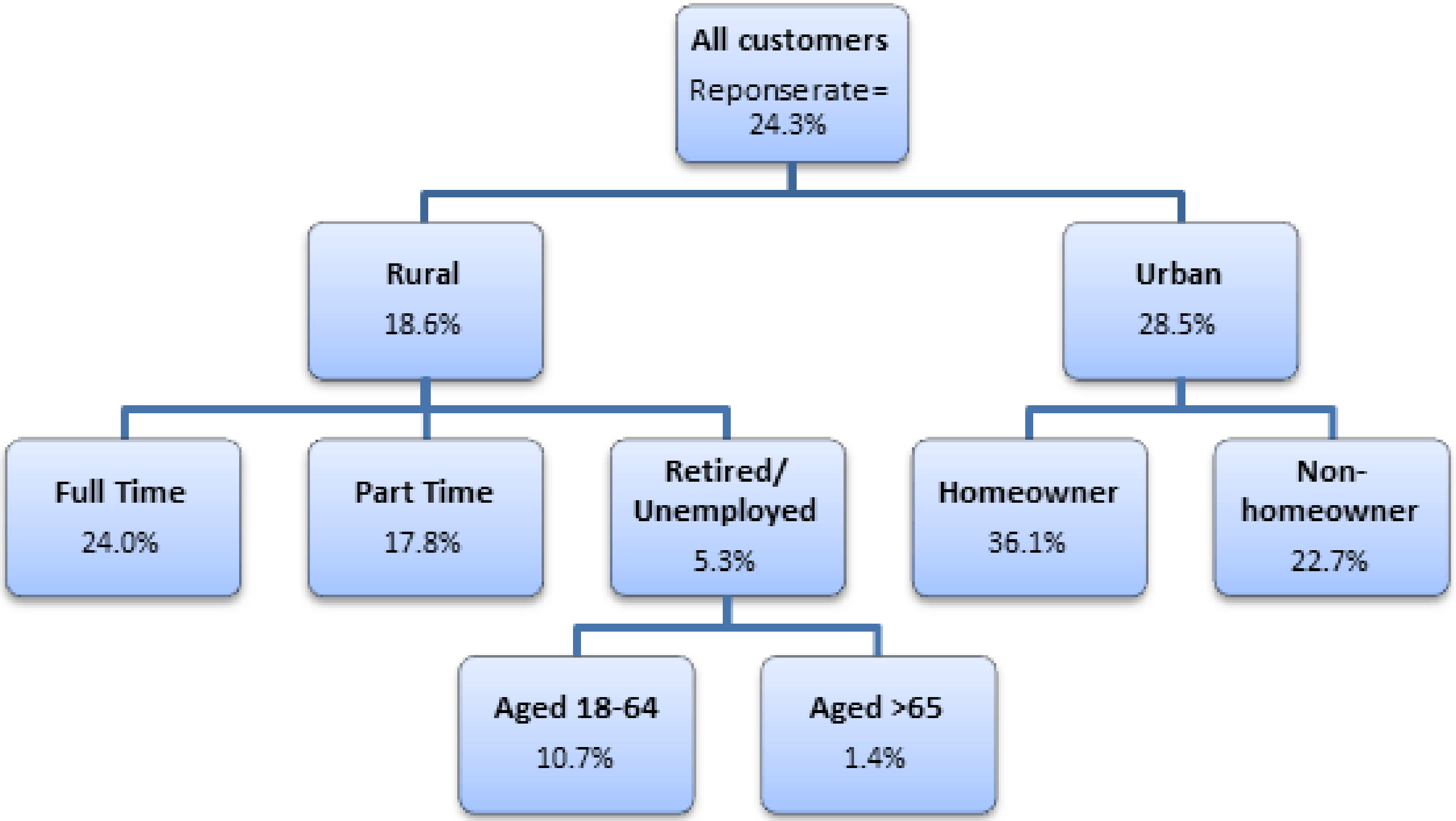
Segmentation – Chi-squared Automatic Interaction Detection (CHAID)



- **All customers** Reponserate= 24.3%
  - **Rural** 18.6%
    - **Full Time** 24.0%
    - **Part Time** 17.8%
    - **Retired/ Unemployed** 5.3%
      - **Aged 18-64** 10.7%
      - **Aged >65** 1.4%
  - **Urban** 28.5%
    - **Homeowner** 36.1%
    - **Non-homeowner** 22.7%

This process helps us tailor marketing strategies to specific subgroups to improve response rates and overall campaign effectiveness.

- Dependent-variable (DV) : Response for a marketing campaign
- Dependent variable is response rate
- The best split can be based on location: rural & urban; working mode; age

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Segmentation (Continued)

- Product-based clusters / category-based clusters
  - → What products do customer buy?
  - → Decide which offerings or marketing communication message to send to each of these types of customers
- Brand-based clusters
  - → What brands people are most likely to buy
- Behaviour-based clusters
  - → How do customers behave?

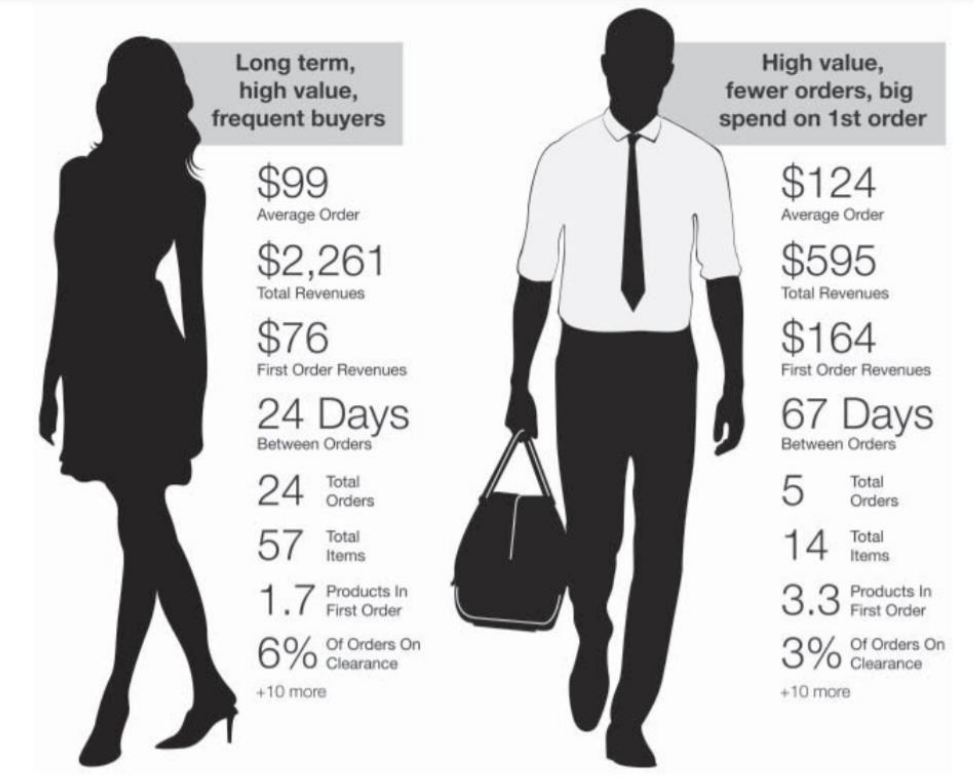

Figure 6.3 Example of Behavior-Based Clusters

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Segmentation – Things to Watch Out

- One-dimensional segmentation is not sufficient
- No person belongs to only one segment
- Segmentation is very contextual. A customer may belong to different segments depending on the situation.

→ E.g., from a product perspective, we consider John to be a runner and Mary to be a swimmer. However, John could also be a discount-sensitive buyer always hunting for deals from a behavioral perspective and Mary always buys the latest product when it first comes out at a full price.

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Basket Analysis on Aggregate Level

- Establish patterns across purchases:

IF {sandwich} THEN {drink}

The items on the right (sandwich) are likely to be ordered with the items on the left (drink)

The item on the left-hand side (sandwich) is the **antecedent** of the rule, while the one on the right-hand side (drink) is the **consequent**

The **probability** that the antecedent event will occur is the **support** of the rule

The **probability** that a customer will purchase a drink on the condition of purchasing a sandwich is referred to as the **confidence** of the rule

Confidence can be used for **product placement strategy** and increasing probability

Placing high margin items near associated high confidence (driver) items can increase the overall margin on purchases

Sandwich → Drink ?

Assume there are 100 customers, 10 of them bought sandwich, 8 bought drink and 6 bought both of them

Support = P(Sandwich) = 10/100 = 0.1

Confidence = P(Sandwich&Drink)/P(Sandwich) = 0.06/0.1 = 0.6

Basket Analysis on Aggregate Level

❖ Establish patterns across purchases:

The **lift** of the rule is the ratio of the support of the left-hand side of the rule (sandwich, cookies) co-occurring with the right-hand side (drink), divided by the probability that the left-hand side and right-hand side co-occur if the two are independent.

lift > 1: the presence of the antecedent increases the chance that the consequent will occur

lift = 1: purchasing the antecedent makes no difference on the chance of purchasing the consequent

lift < 1: purchasing the antecedent reduces the chance of purchasing the consequent (maybe the items are alternatives to each other)

Sandwich → Drink ?

Assume there are 100 customers, 10 of them bought sandwich, 8 bought drink and 6 bought both of them

Support = P(Sandwich) = 10/100 = 0.1

Confidence = P(Sandwich&Drink)/P(Sandwich) = 0.06/0.1 = 0.6

Lift = Confidence/P(Drink) = 0.6/0.08 = 7.5

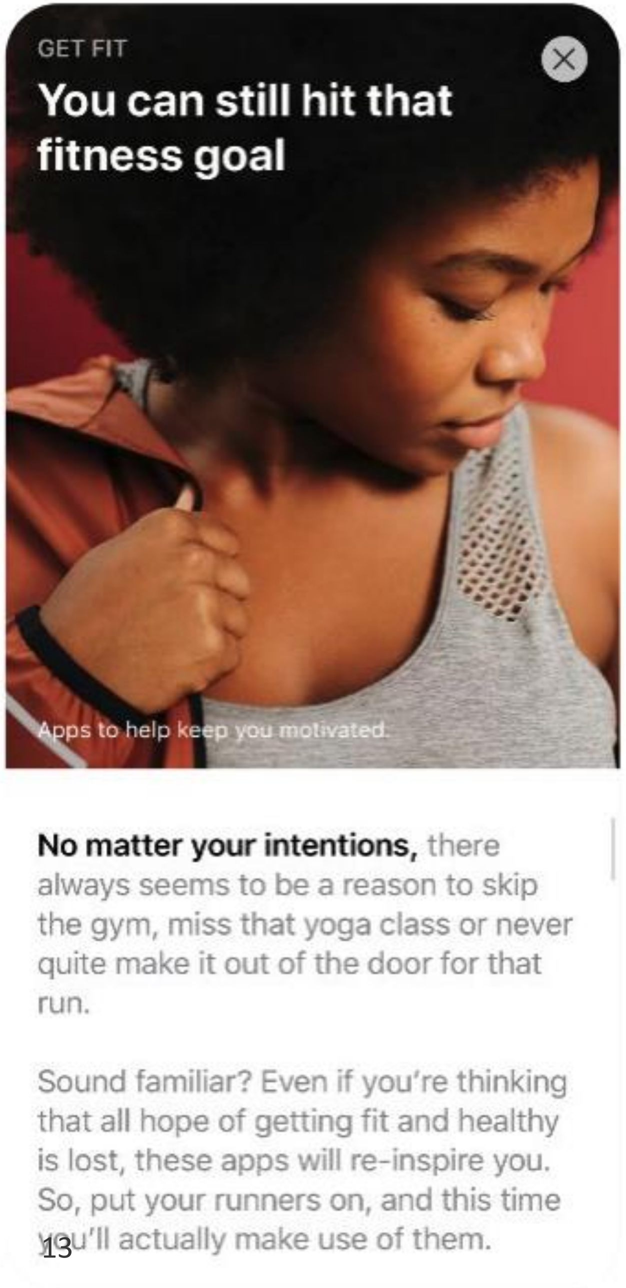
Basket Analysis on Aggregate Level

LHS	RHS	rules	support	confidence	lift
Ice Cream	Soda	{Ice Cream} => {Soda}	0.07	1.00	5.00
Soda	Ice Cream	{Soda} => {Ice Cream}	0.07	0.33	5.00
Ice Cream	Pie	{Ice Cream} => {Pie}	0.07	1.00	3.00
Pie	Ice Cream	{Pie} => {Ice Cream}	0.07	0.20	3.00
Ice Cream	Burger	{Ice Cream} => {Burger}	0.07	1.00	2.50
Burger	Ice Cream	{Burger} => {Ice Cream}	0.07	0.17	2.50
Ice Cream	Salad	{Ice Cream} => {Salad}	0.07	1.00	2.14
Salad	Ice Cream	{Salad} => {Ice Cream}	0.07	0.14	2.14
Ice Cream	Pizza	{Ice Cream} => {Pizza}	0.07	1.00	2.14
Pizza	Ice Cream	{Pizza} => {Ice Cream}	0.07	0.14	2.14
Soda	Chicken	{Soda} => {Chicken}	0.07	0.33	1.67
Chicken	Soda	{Chicken} => {Soda}	0.07	0.33	1.67
Soda	Chocolate Shake	{Soda} => {Chocolate Shake}	0.07	0.33	1.25
Chocolate Shake	Soda	{Chocolate Shake} => {Soda}	0.07	0.25	1.25
Soda	Pie	{Soda} => {Pie}	0.20	1.00	3.00
Pie	Soda	{Pie} => {Soda}	0.20	0.60	3.00
Soda	Burger	{Soda} => {Burger}	0.20	1.00	2.50
Burger	Soda	{Burger} => {Soda}	0.20	0.50	2.50
Soda	Bottled Water	{Soda} => {Bottled Water}	0.07	0.33	0.83
Bottled Water	Soda	{Bottled Water} => {Soda}	0.07	0.17	0.83
Soda	Salad	{Soda} => {Salad}	0.20	1.00	2.14
Salad	Soda	{Salad} => {Soda}	0.20	0.43	2.14
Soda	Pizza	{Soda} => {Pizza}	0.20	1.00	2.14

- **What can you tell?**

Basket Analysis on Aggregate Level

- Product placement: identifying products that may often be purchased together and arranging the placement of those items close by to encourage purchase of both items (e.g., in catalog or on website)



GET FIT

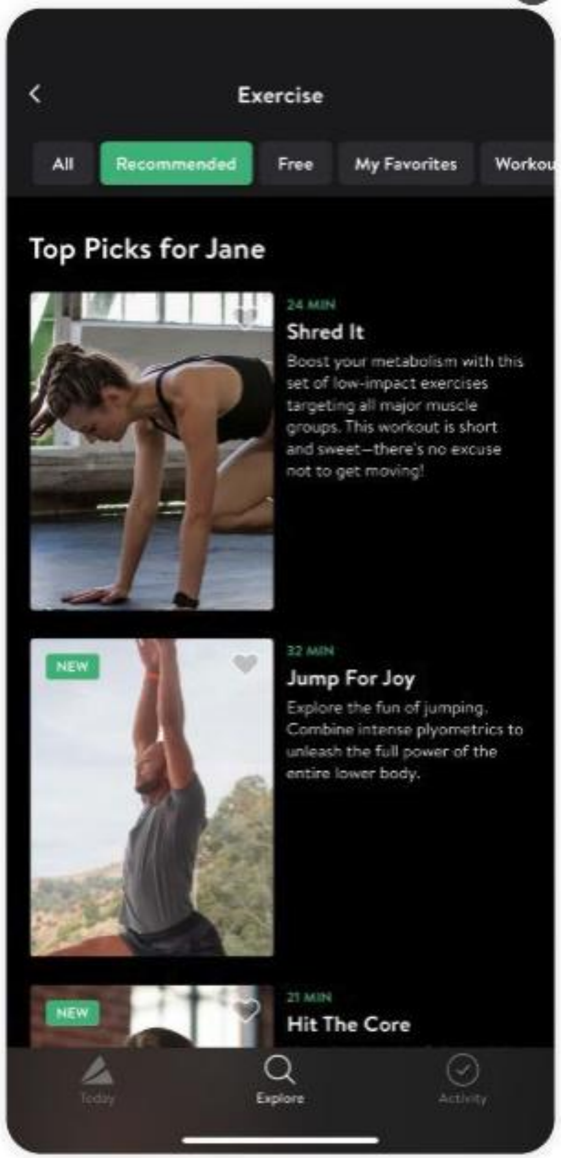
You can still hit that fitness goal

Apps to help keep you motivated.

No matter your intentions, there always seems to be a reason to skip the gym, miss that yoga class or never quite make it out of the door for that run.

Sound familiar? Even if you're thinking that all hope of getting fit and healthy is lost, these apps will re-inspire you. So, put your runners on, and this time you'll actually make use of them.

Make a plan



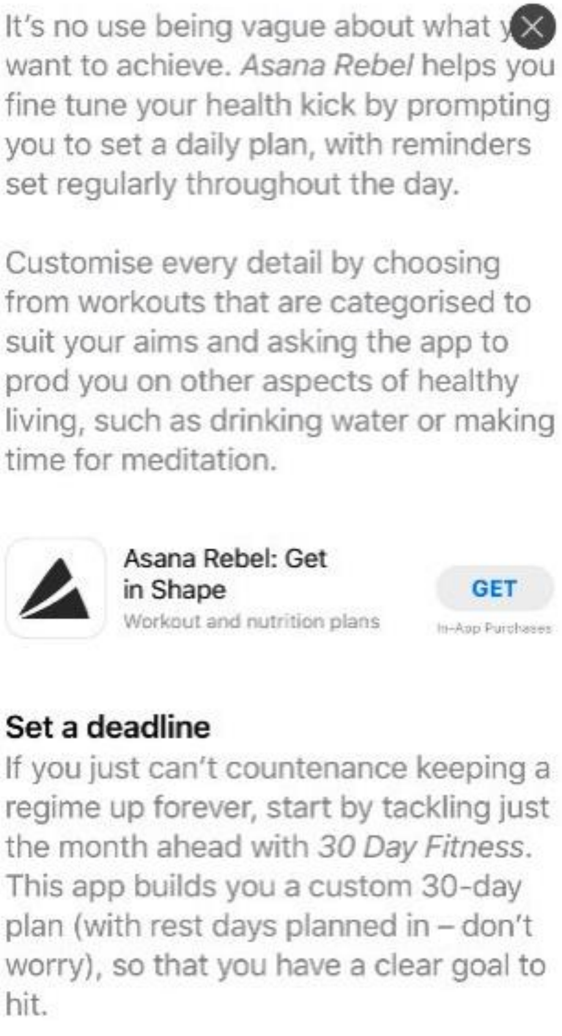
Top Picks for Jane

24 MIN
Shred It
Boost your metabolism with this set of low-impact exercises targeting all major muscle groups. This workout is short and sweet—there's no excuse not to get moving!

32 MIN
Jump For Joy
Explore the fun of jumping. Combine intense plyometrics to unleash the full power of the entire lower body.

21 MIN
Hit The Core

Asana Rebel is fully customised to suit your needs.



It's no use being vague about what you want to achieve. *Asana Rebel* helps you fine tune your health kick by prompting you to set a daily plan, with reminders set regularly throughout the day.

Customise every detail by choosing from workouts that are categorised to suit your aims and asking the app to prod you on other aspects of healthy living, such as drinking water or making time for meditation.

Asana Rebel: Get in Shape
Workout and nutrition plans
GET
In-App Purchases

Set a deadline

If you just can't countenance keeping a regime up forever, start by tackling just the month ahead with *30 Day Fitness*. This app builds you a custom 30-day plan (with rest days planned in – don't worry), so that you have a clear goal to hit.

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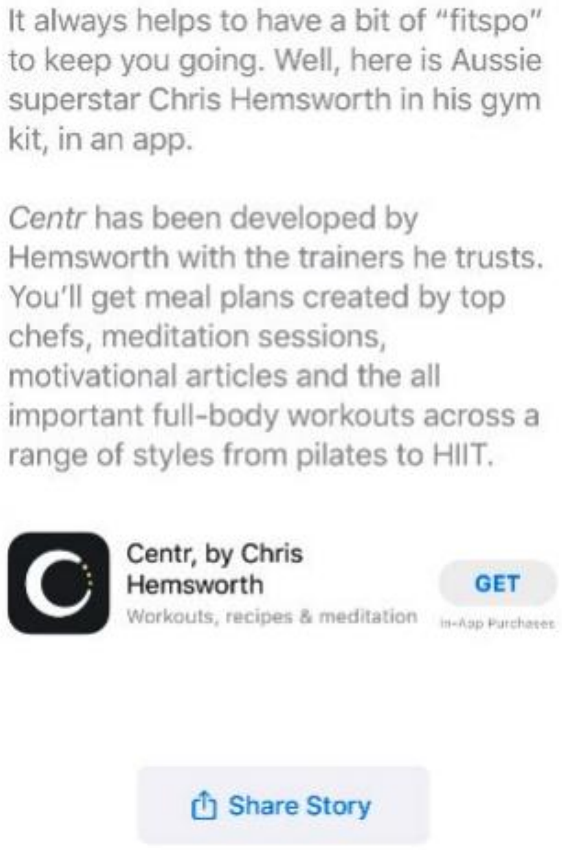


It always helps to have a bit of "fitspo" to keep you going. Well, here is Aussie superstar Chris Hemsworth in his gym kit, in an app.

Centr has been developed by Hemsworth with the trainers he trusts. You'll get meal plans created by top chefs, meditation sessions, motivational articles and the all important full-body workouts across a range of styles from pilates to HIIT.

Centr, by Chris Hemsworth
Workouts, recipes & meditation
GET
In-App Purchases

Share Story

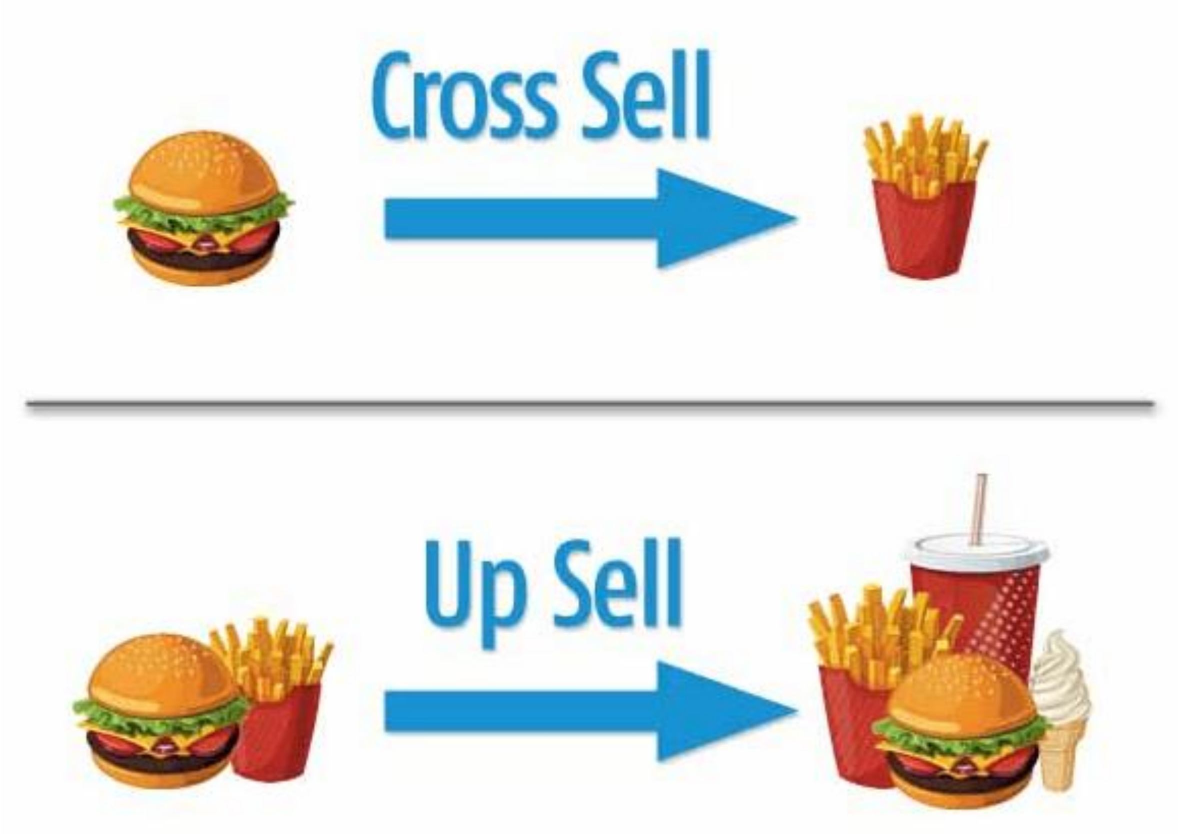
Basket Analysis on Aggregate Level

- Physical shelf arrangement: separating items that are often purchased together to encourage individuals to wander through the store to find what they are looking for to potentially increase the probability of additional impulse purchases

by Bingqing Xiong

Basket Analysis on Aggregate Level

- Up-sell, cross-sell, bundling: companies may use the affinity grouping of multiple products as an indication that customers may be predisposed to buying the grouped products at the same time.
- This enables the presentation of items for cross-selling, or may suggest that customers may be willing to buy more items when certain products are bundled together.



Basket Analysis on Aggregate Level

- Customer retention: the basket analysis may also help company to determine the right incentives to offer in order to retain certain customers.

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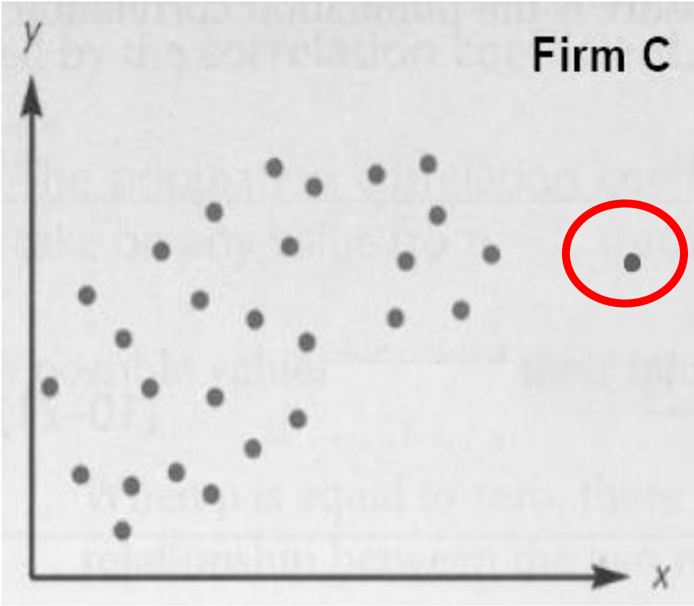
Correlation Analysis

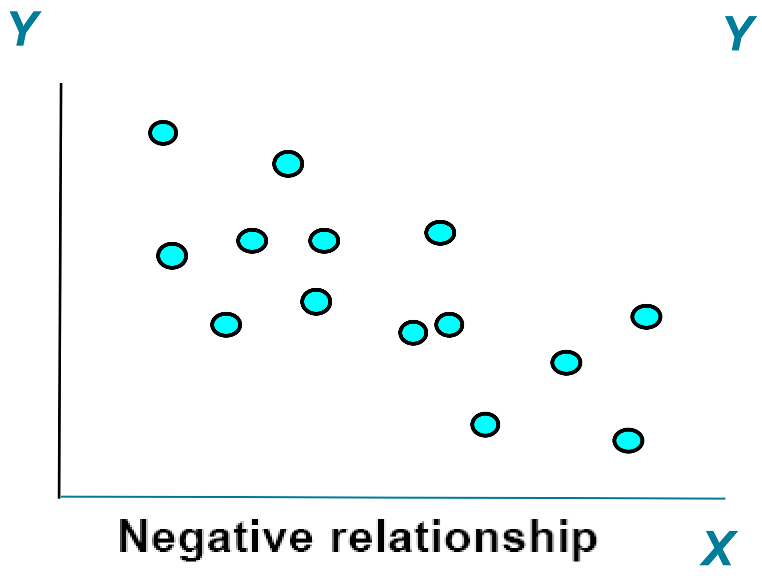
First step to investigate the nature of relationship between 2 variables is to visualize - Scatter plot

E.g. Advertising (X) and Sales (Y) of firms over time

Direction of association - Positive or Negative

Scatter plot could also help to identify the outliers





Negative relationship

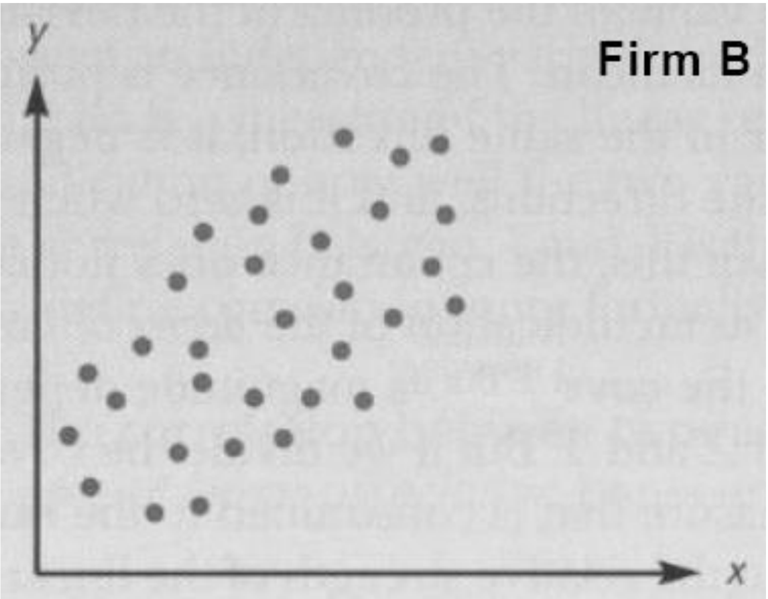
Positive relationship

Correlation Analysis

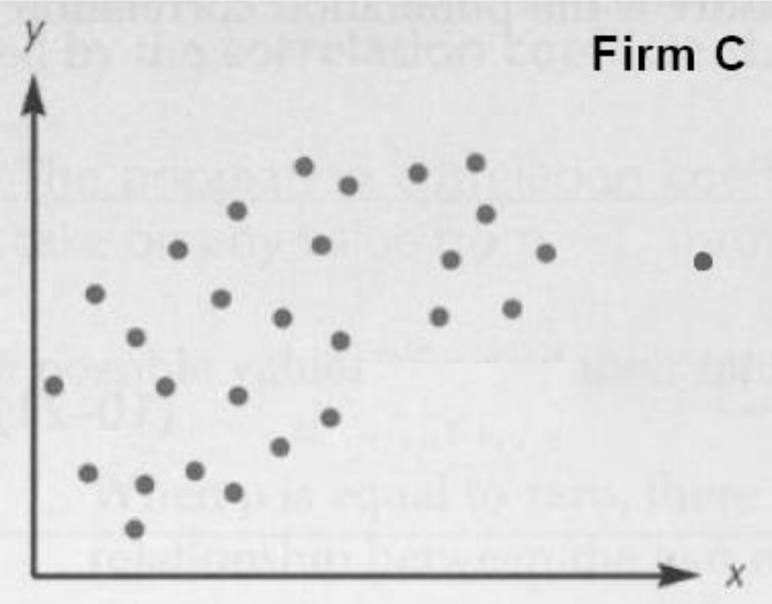
First step to investigate the nature of relationship between 2 variables is to visualize - Scatter plot

E.g. Advertising (X) and Sales (Y) of firms over time

- Strength of association



Positive relationship



Positive relationship

- Sometimes difficult to say with eyes, we need a measure
- **Pearson Correlation Coefficient**

The (Pearson) Correlation Coefficient Explained in One Minute: From Definition to Formula + Examples

Correlation Analysis

A measure of both strength and direction, calculated as the covariance of X and Y divided by the standard deviation of X * the standard deviation of Y

The strength of association is determined by the size of the correlation coefficient

Larger coefficients, stronger association

$$\rho = \frac{Covar(x,y)}{SxSy}$$

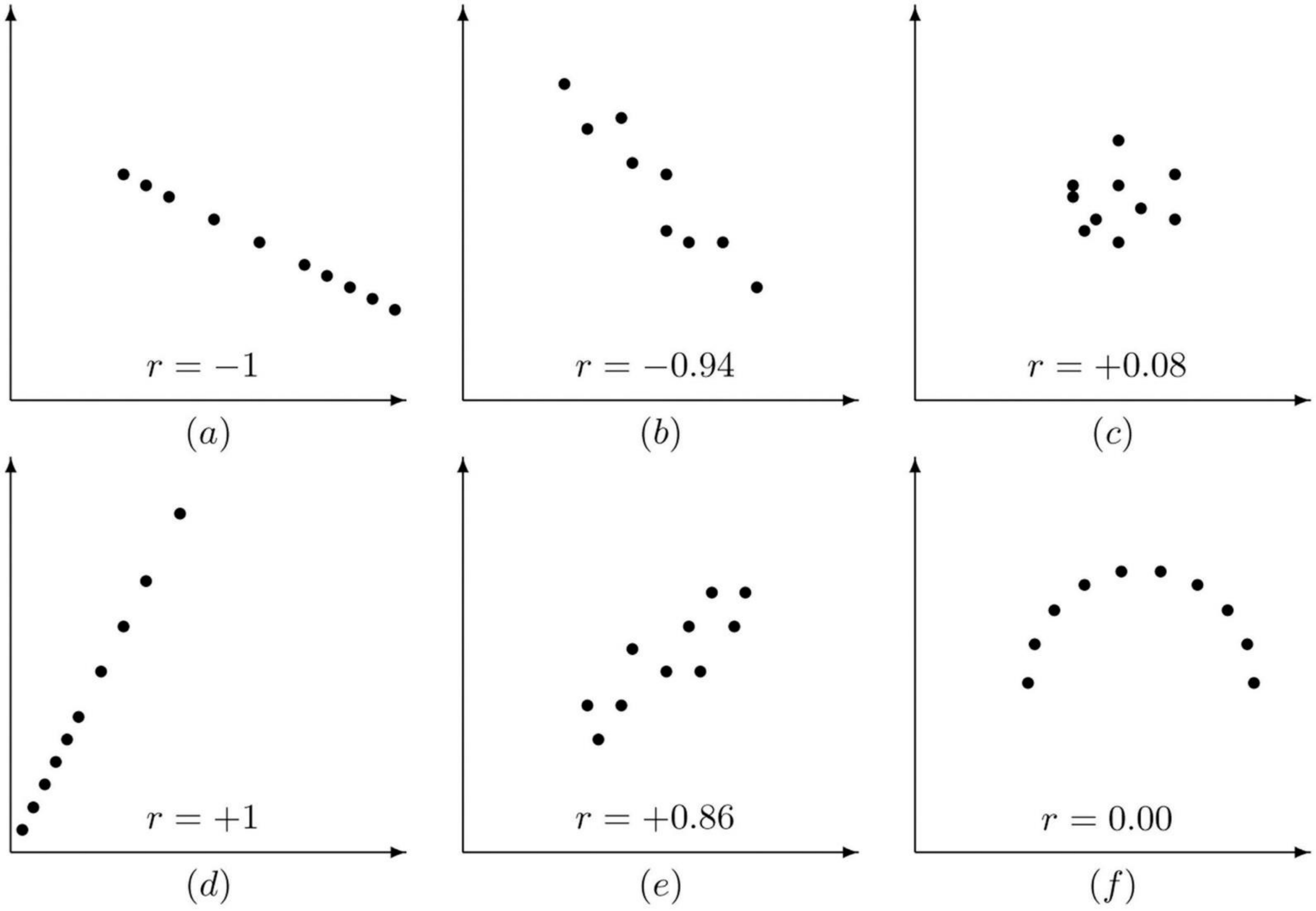
Correlation Analysis

Correlation coefficient summarizes the **strength of association** between two metric (interval or ratio scaled) variables, say *X* and *Y*.

Values of *r* is between -1 and 1

- $r = 0$: no relationship between the 2 variables
- $r > 0$: there is a positive relationship
- $r < 0$: there is a negative relationship
- $r = 1$: perfectly and positively related
- $r = -1$: perfectly and negatively related
- The closer *r* is to -1 or 1, the stronger is the relationship

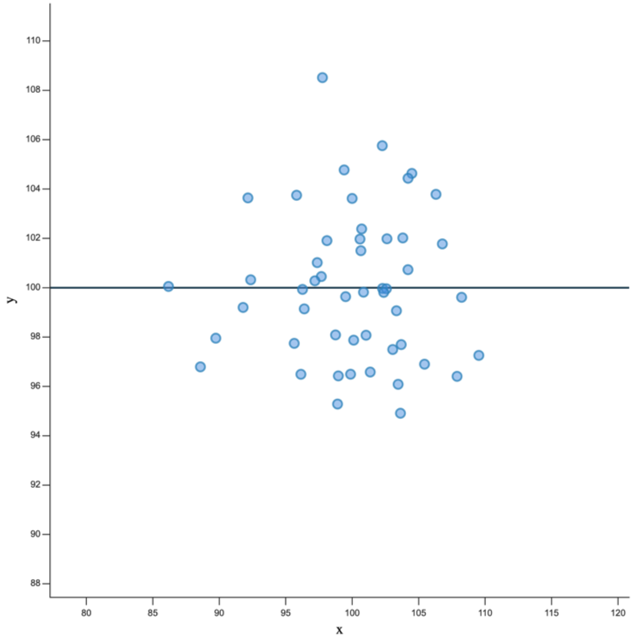
Correlation Analysis



(a) (b) (c)

(d) (e) (f)

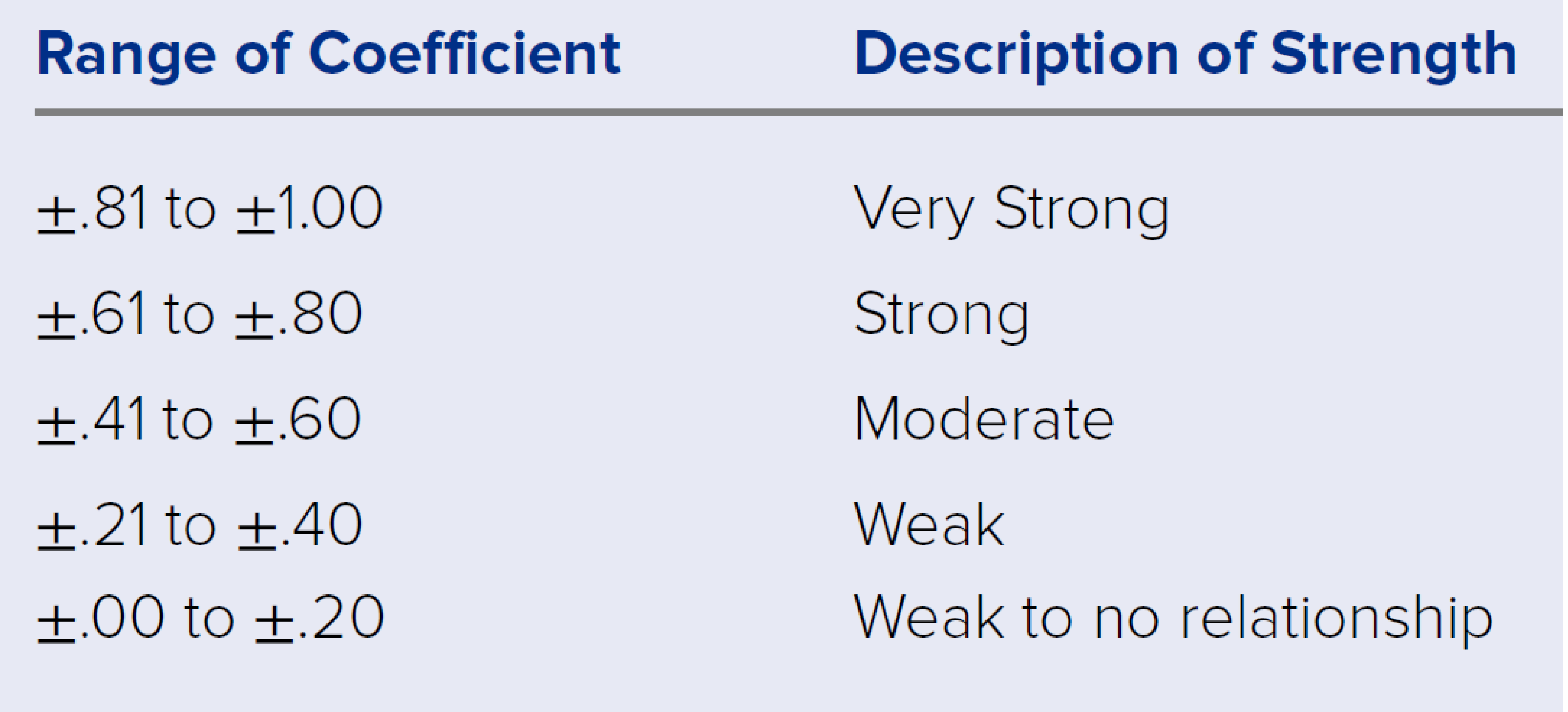
What’s the correlation coefficient ?



An interactive tool: https://rpsychologist.com/correlation/

Correlation Analysis

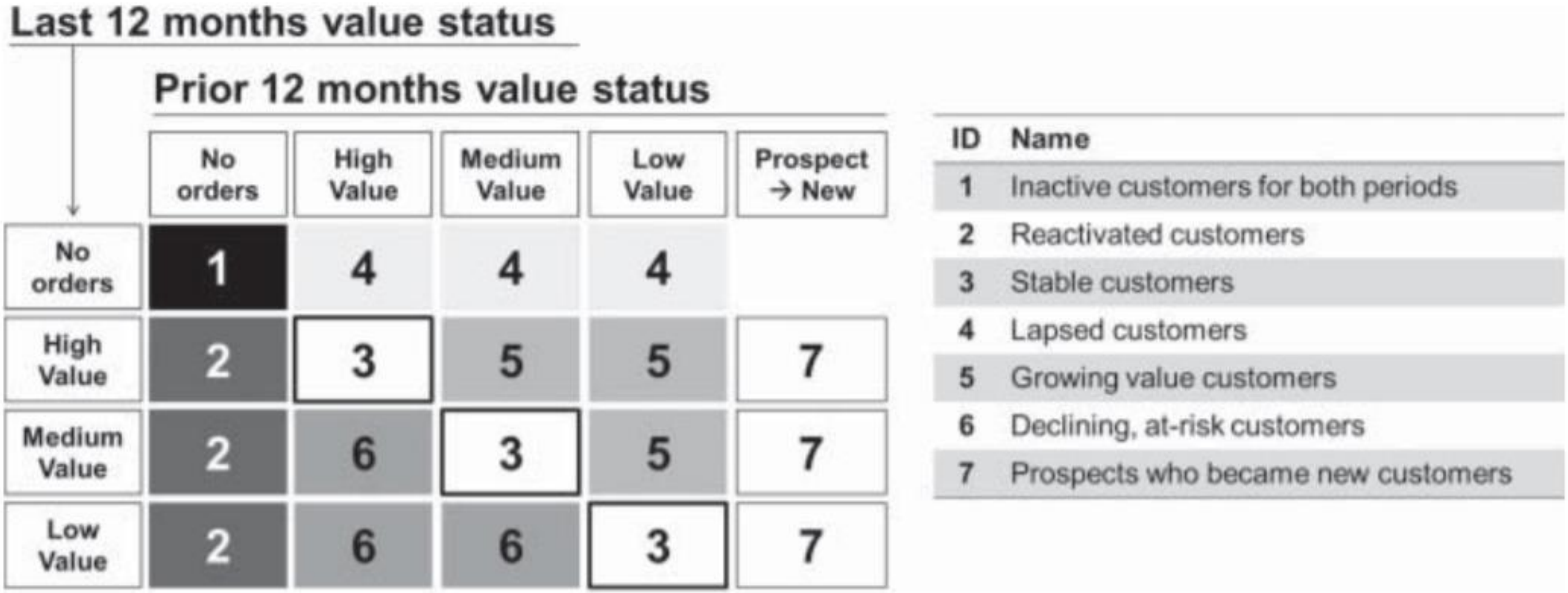
Rules of thumb for characterizing the strength of the association between two variables based on the size of the correlation coefficient are suggested



Range of Coefficient	Description of Strength
±.81 to ±1.00	Very Strong
±.61 to ±.80	Strong
±.41 to ±.60	Moderate
±.21 to ±.40	Weak
±.00 to ±.20	Weak to no relationship

Value Transition

- Value-transition and Definition of Value Segments



Last 12 months value status

Prior 12 months value status

	No orders	High Value	Medium Value	Low Value	Prospect → New
No orders	1	4	4	4	
High Value	2	3	5	5	7
Medium Value	2	6	3	5	7
Low Value	2	6	6	3	7

ID	Name
1	Inactive customers for both periods
2	Reactivated customers
3	Stable customers
4	Lapsed customers
5	Growing value customers
6	Declining, at-risk customers
7	Prospects who became new customers

Useful Transaction Information

❖ Sales:

Total/Annual total number of purchases?

Whether seasonal? How?

Purchase break down by access device / channels?

❖ Customer profiles:

Who are buying certain types of product?

Who are profitable?

Who are active and/or loyal buyers (bought recently; bought frequently)?

How many customers in each customer-based/product-based/behaviour-based cluster?

Who are seasonal customers?

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Strategies

- **Products generally bought together**

Upselling, cross-selling, bundling, etc.

- **Increase customer lifetime value**

Acquire – attract more valuable customers

Grow & Retain

Prevent Churn

Engage (Certain) Customers

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Strategies

New Customer Strategies: Thank You

Thank you letter / sticker

Provide useful tips on how to use or maintain new products

Customer service representatives ask for feedback on product / purchase experience

Repeat/Active Customer Strategies: We Love You

Appreciate the best customers

Create treatment strategies (e.g., Amazon sent coffee mugs to loyal customers around Christmas holidays)

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Strategies

❖ Inactive Customer Strategies: Remember Me

Investigate the reason why this (group of) customer(s) stopped buying or using your offerin
(e.g., phone calls, email surveys, etc.)

Offer constant gentle reminder and provide gentle nudge to come back again

Send recommendations

‘We miss you’ & give reasons to come back (e.g., discount)

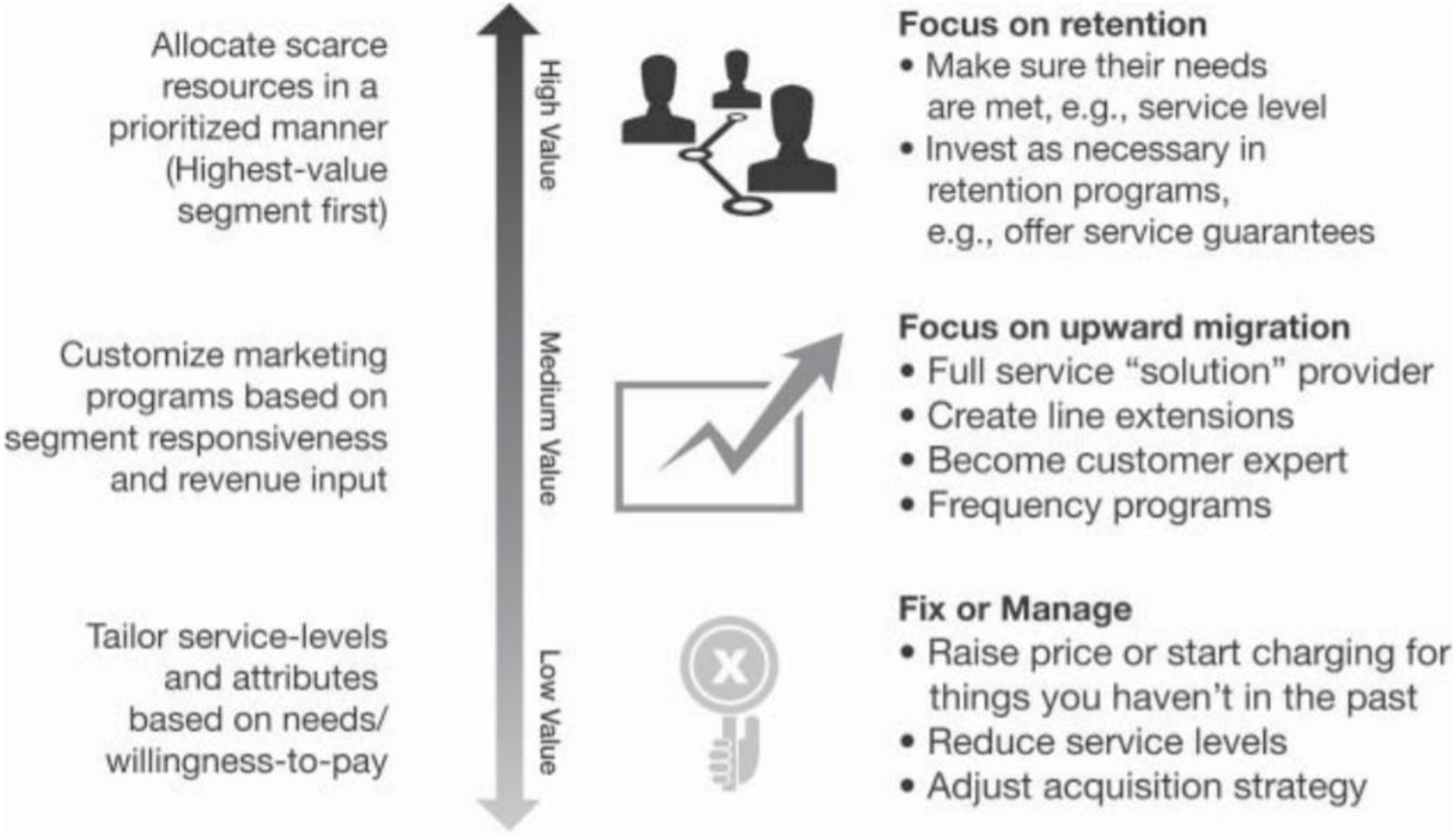
❖ Lapsed Customer Strategies: We Miss You

Strong offer can be more important than personalized recommendations and reminders

Try reach these customers through different channels

Strategies

- ❖ Value-based Marketing Strategies



Allocate scarce resources in a prioritized manner (Highest-value segment first)

Focus on retention
- Make sure their needs are met, e.g., service level
- Invest as necessary in retention programs, e.g., offer service guarantees

Customize marketing programs based on segment responsiveness and revenue input

Focus on upward migration
- Full service "solution" provider
- Create line extensions
- Become customer expert
- Frequency programs

Tailor service-levels and attributes based on needs/ willingness-to-pay

Fix or Manage
- Raise price or start charging for things you haven't in the past
- Reduce service levels
- Adjust acquisition strategy

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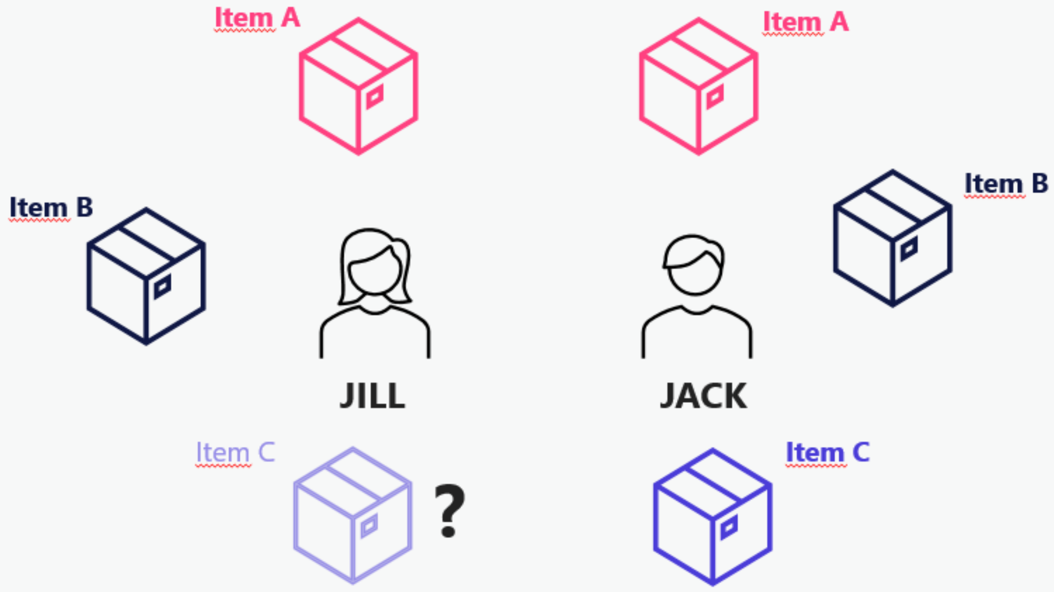
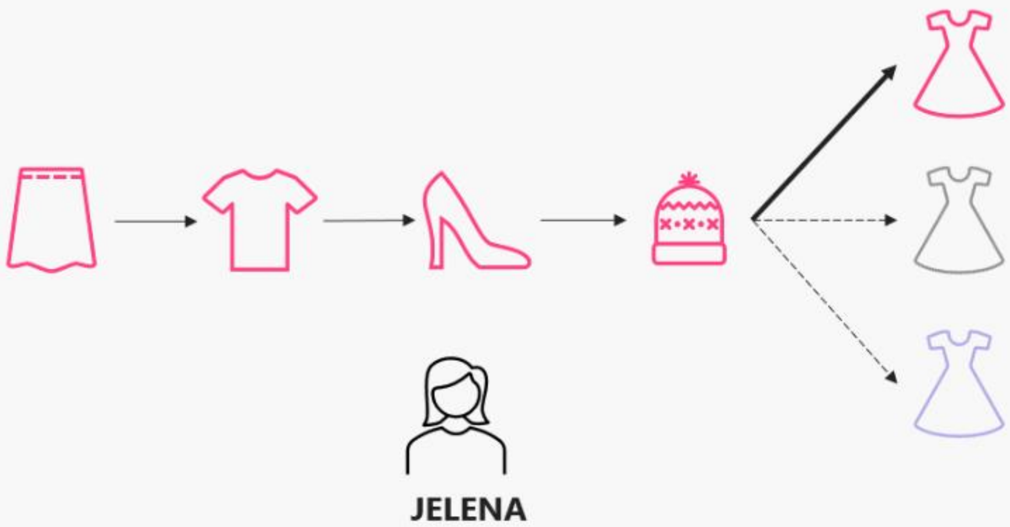
Application: Product Recommendation System

- Analyzing transactional data to identify patterns and trends in customer behaviour.
- Marketers can design a product recommendation system that is tailored to each individual customer's preferences and behaviour.
- **Collaborative filtering** and **content-based filtering** are two techniques that can be used to design a product recommendation system.
- By combining these techniques and other data-driven approaches, marketers can develop a sophisticated product recommendation system that takes into account a wide range of factors.
- A personalized and relevant product recommendation system can help increase engagement, loyalty, and sales.





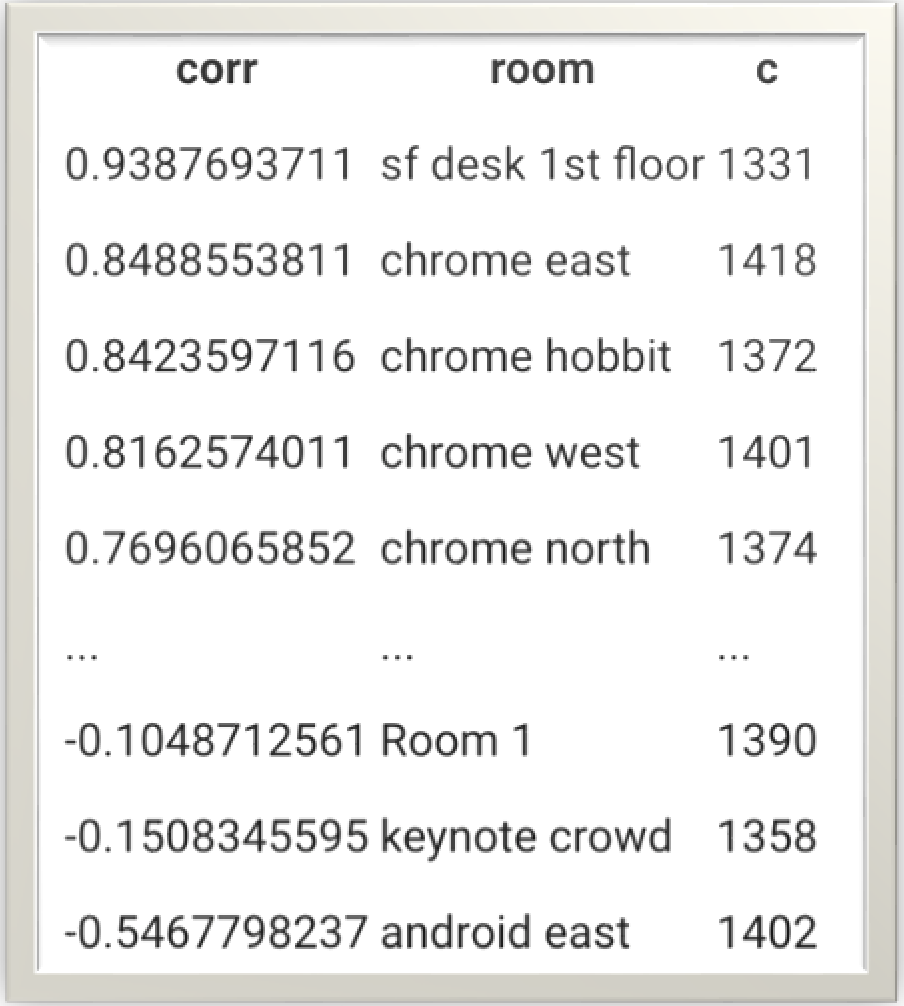
Source: https://www.be-terna.com/insights/recommendation-systems-in-e-commerce-whats-the-thing-youve-never-known-but-always-wanted-to

To Sum Up

- Transaction Data: Assess and characterize purchase dynamics
- Segmentation
- Perform relevant analysis and interpret the results: RFM Analysis, CLV, Correlation Analysis
- Strategy


thank
you

After Class Reading: Correlation Analysis in BigQuery



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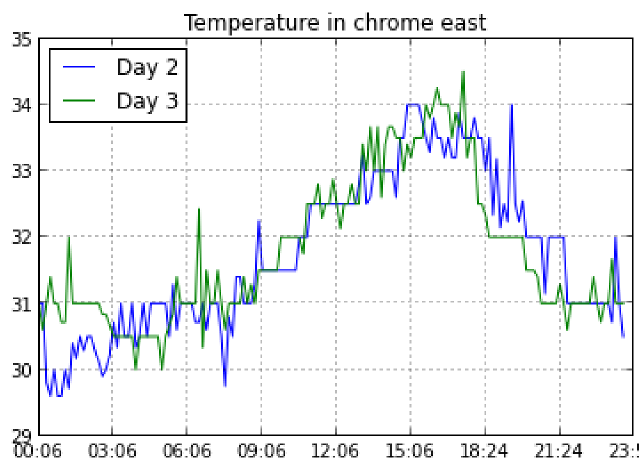

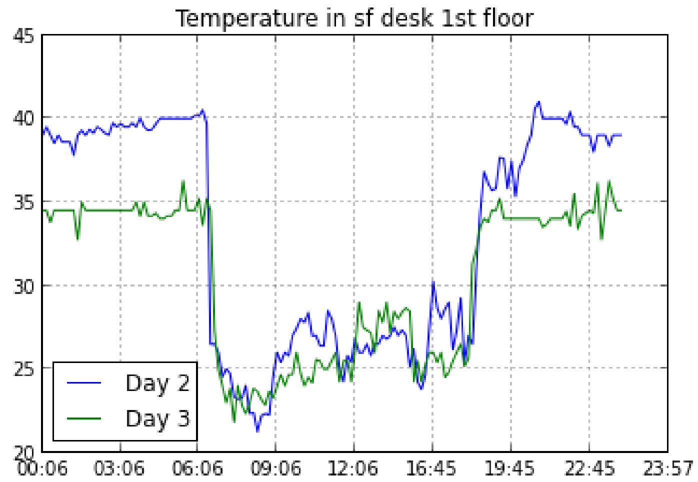

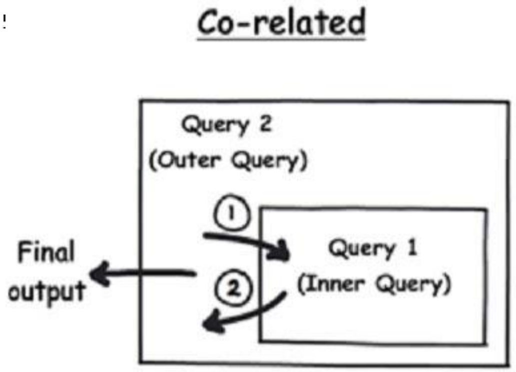

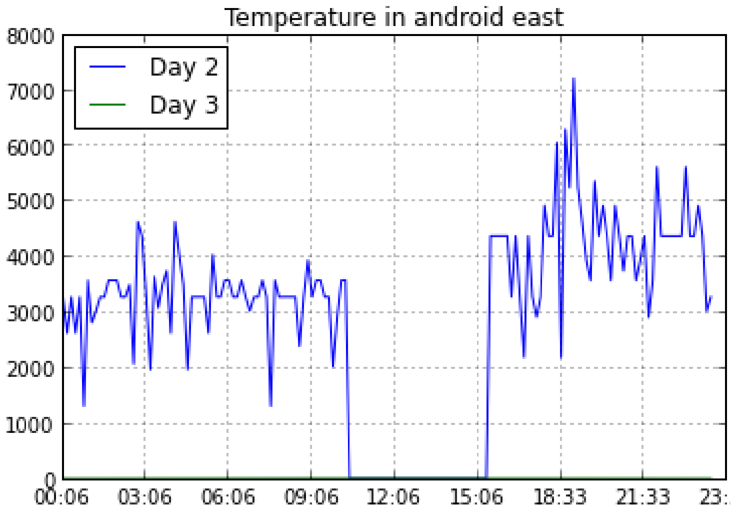

Source: https://cloudplatform.googleblog.com/2013/09/introducing-corr-to-google-bigquery.html