DATA ANALYTICS FOR HUMAN RESOURCE MANAGEMENT

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LOOKING FURTHER

INTRODUCTION

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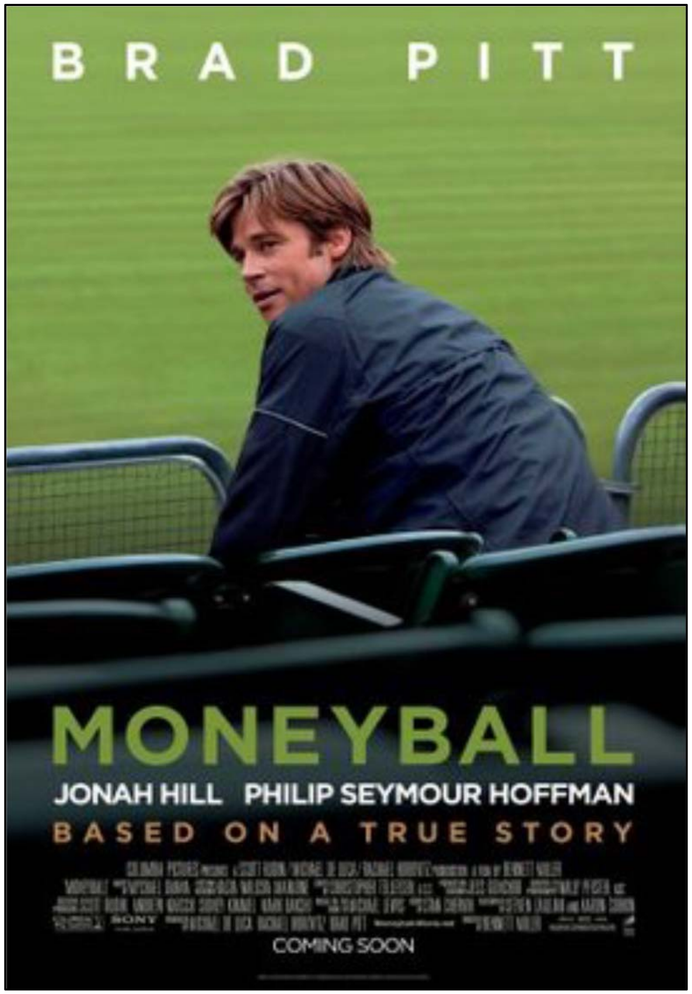
Business Analytics: Optimization of Business Processes

Research / Education:

- Decision making under uncertainty
- Control of complex high-dimensional systems
- Stochastic optimization

RECRUITMENT SUCCESS STORIES?



- "Why do professional baseball executives, many of whom have spent their lives in the game, make so many colossal mistakes? …

  It takes time and effort to switch from simple intuitions to careful assessments of evidence."

  Thaler and Sunstein
  review of Moneyball

ANALYTICS AS INTELLIGENCE AUGMENTATION

Clinical versus actuarial judgment

RM Dawes, D Faust, PE Meehl

+ Author Affiliations

Science 31 Mar 1989:
Vol. 243, Issue 4899, pp. 1668-1674
DOI: 10.1126/science.2648573

Article Info & Metrics eLetters PDF

Abstract

Professionals are frequently consulted to diagnose and predict human behavior; optimal treatment and planning often hinge on the consultant's judgmental accuracy. The consultant may rely on one of two contrasting approaches to decision-making--the clinical and actuarial methods. Research comparing these two approaches shows the actuarial method to be superior. Factors underlying the greater accuracy of actuarial methods, sources of resistance to the scientific findings, and the benefits of increased reliance on actuarial approaches are discussed.

EXAMPLE 1: PUZZLING RELATIONSHIPS

Question:

- Jack is looking at Anne, but Anne is looking at George.
- Jack is married, but George is not.
- Is a married person looking at an unmarried person?

A. Yes

B. No

C. Cannot be determined

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EXAMPLE 1: PUZZLING RELATIONSHIPS

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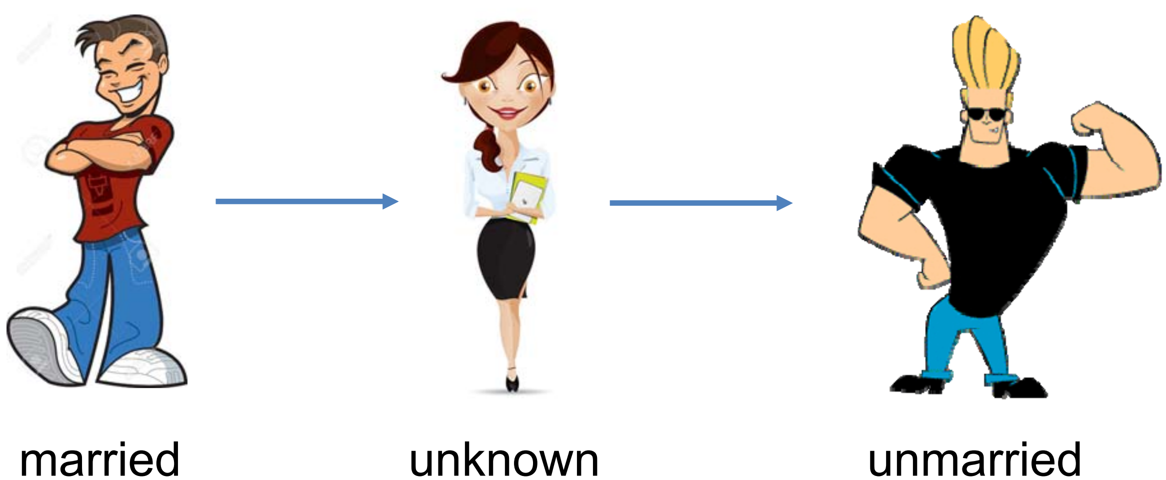
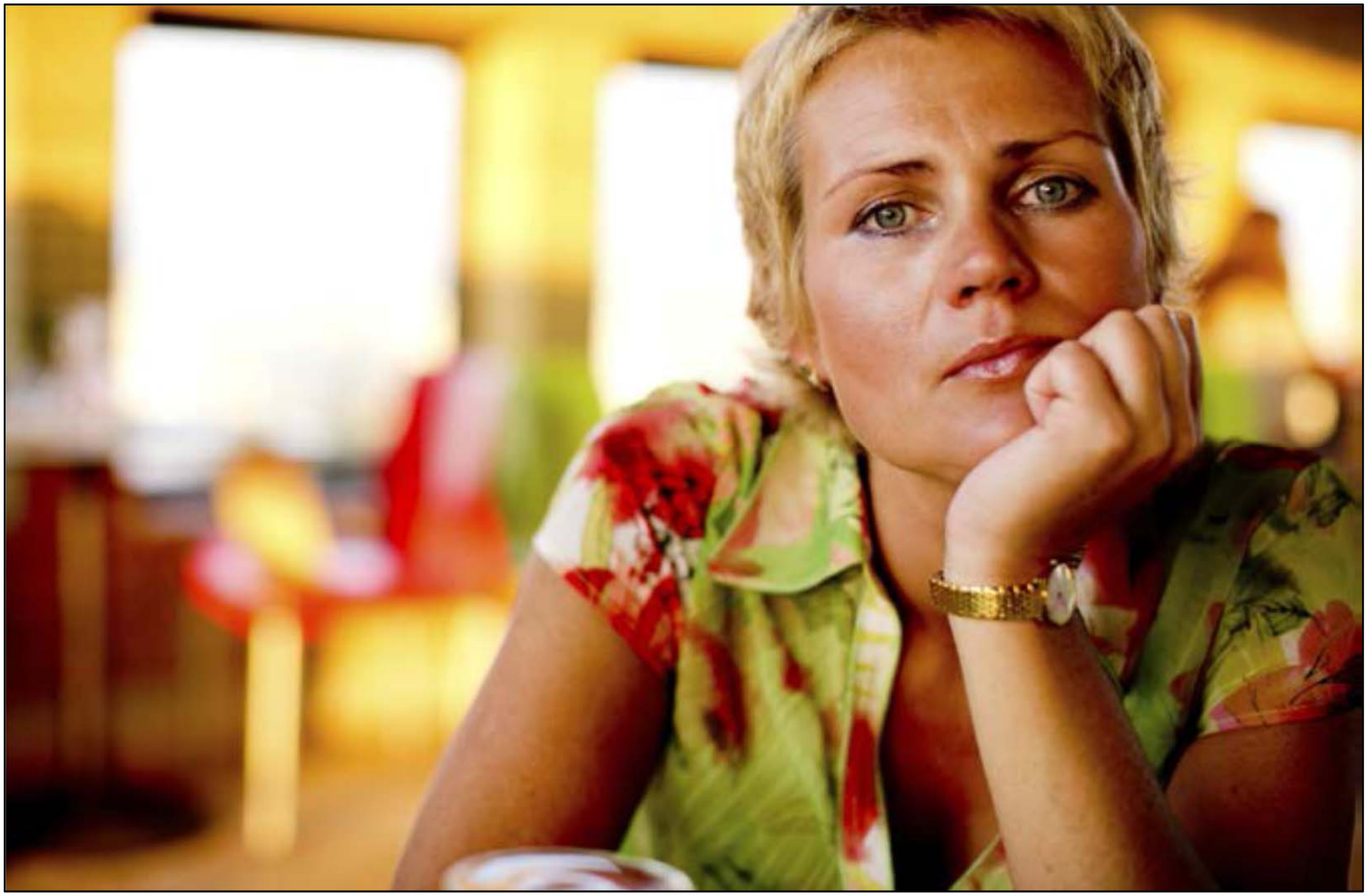
- Is a married person looking at an unmarried person?

A. Yes



EXAMPLE 2: THERE'S SOMETHING ABOUT LINDA



EXAMPLE 2: THERE'S SOMETHING ABOUT LINDA

Examine the following profile:

- Linda is 31 years old, single, outspoken, and very bright. She majored in philosophy. As a student, she was deeply concerned with issues of discrimination and social justice, and also participated in anti-nuclear demonstrations.
- Which of these scenarios is more likely?

A. Linda is a bank teller

B. Linda is a bank teller and is active in the feminist movement

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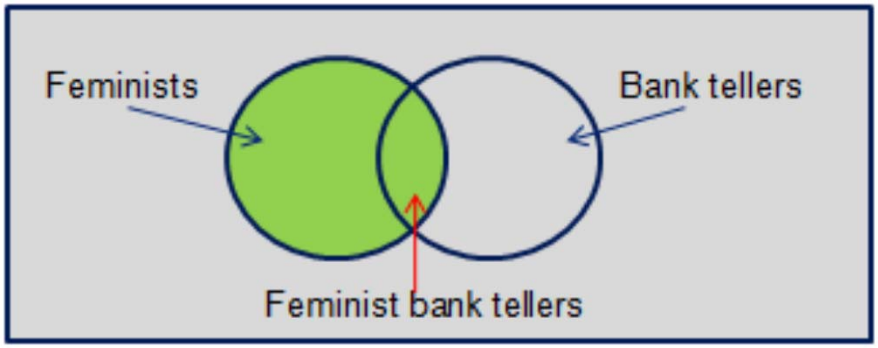
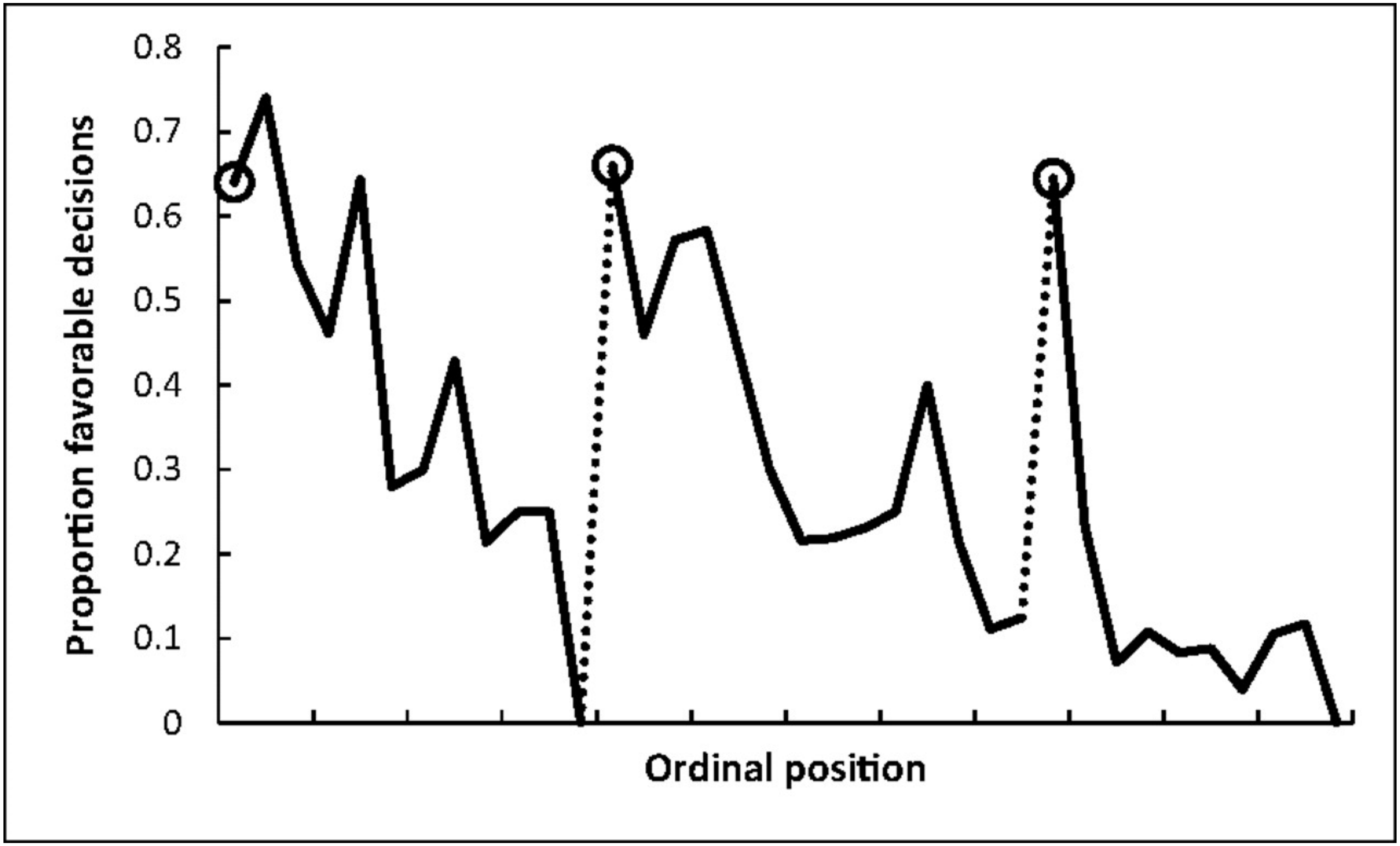


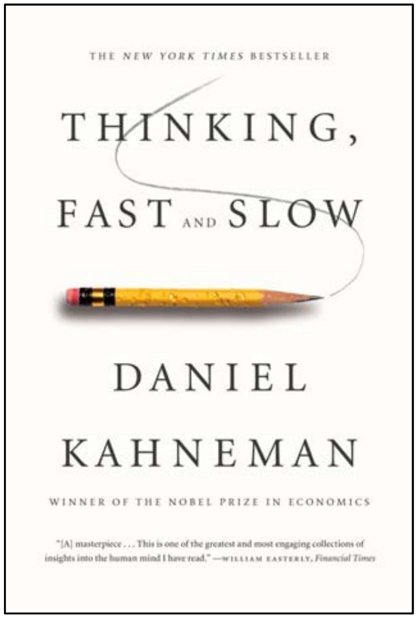
EXAMPLE 3: DECISION FATIGUE

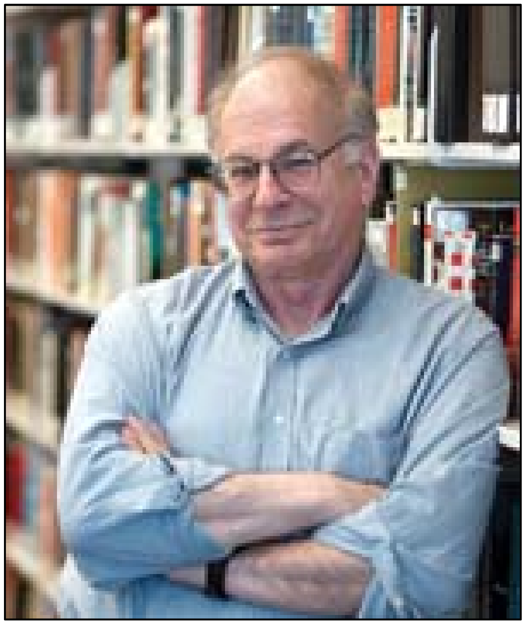


THE MORAL OF THESE EXAMPLES

- There are two types of mental operations:

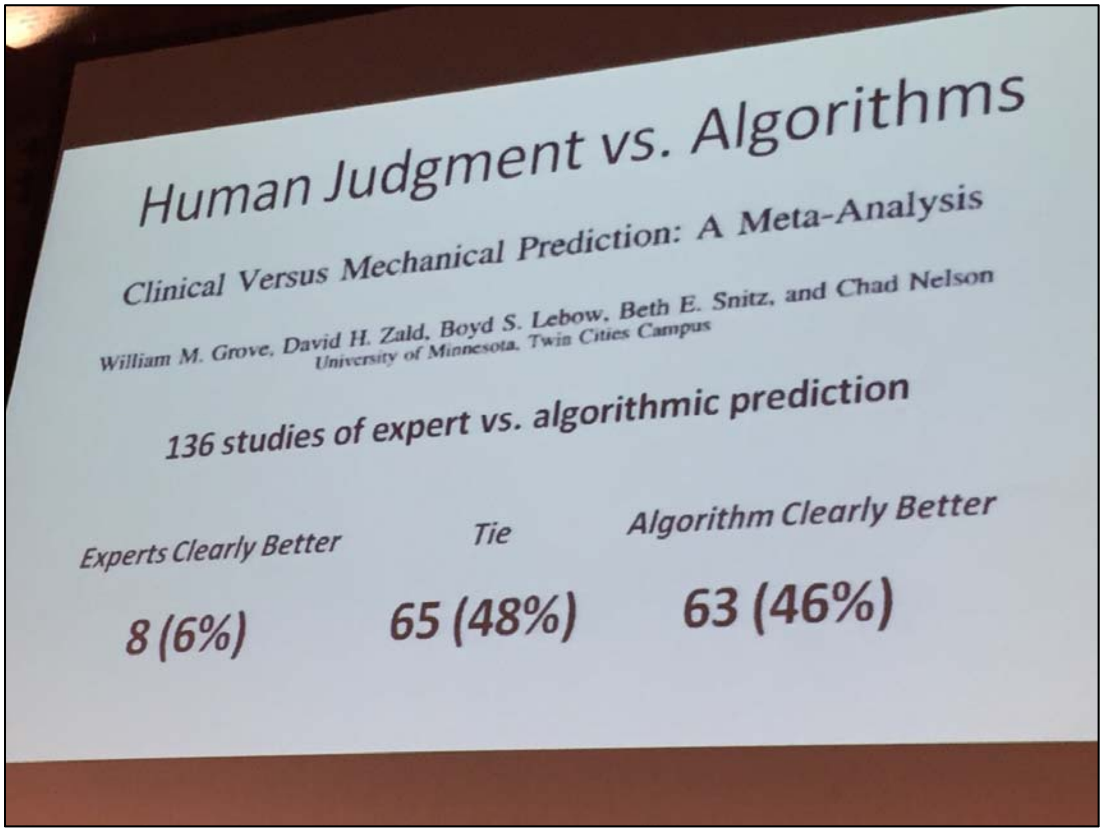
1. Type 1: automatic, effortless, associatively coherent
2. Type 2: controlled, effortful, logically coherent





THE MORAL OF THESE EXAMPLES

- Behavioral economics teaches us that the value of analytics is often in avoiding biased judgments and flawed decisions.



ANALYTICS: SHIFTING PARADIGMS

Do computers play more intelligently than humans?

Geplaatst op 23/10/2014 | *Published in Schaken* | *Reageren*

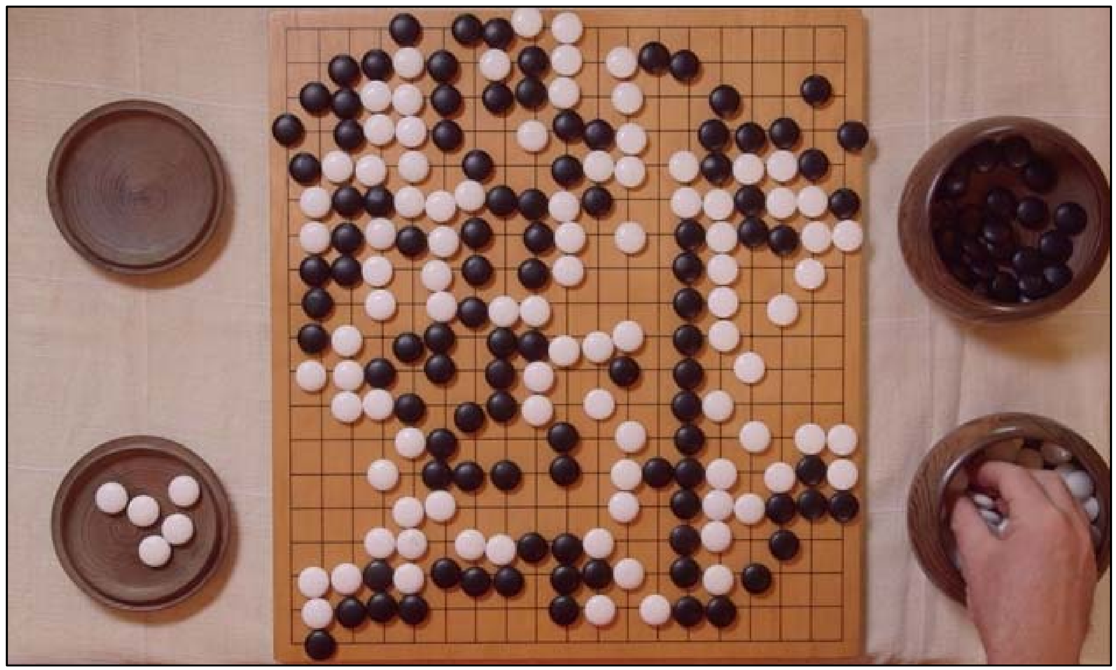
ANALYTICS: SHIFTING PARADIGMS

Google AI algorithm masters ancient game of Go

Deep-learning software defeats human professional for first time.

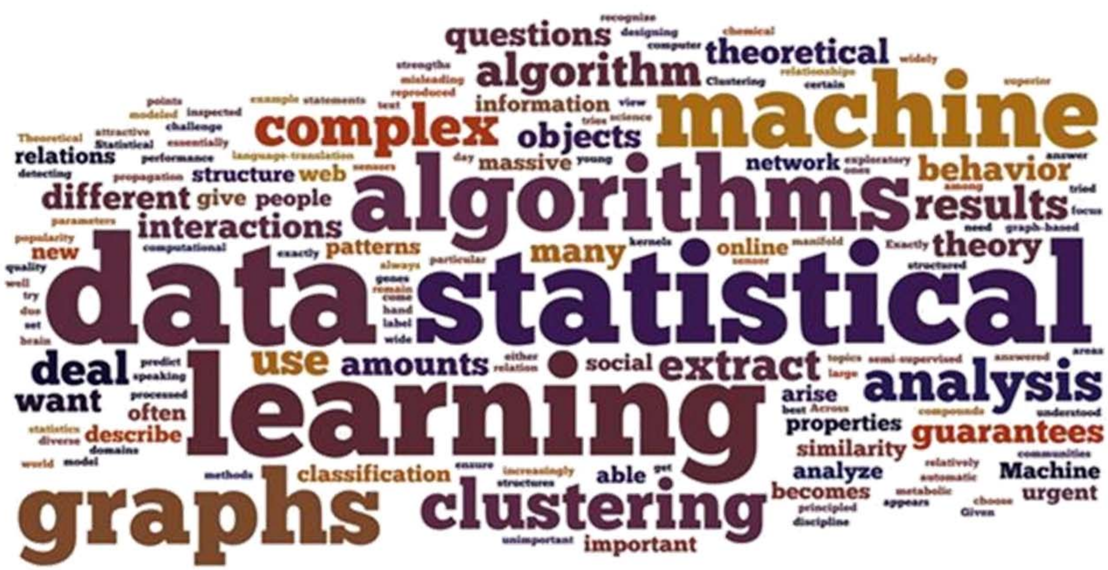
Elizabeth Gibney

27 January 2016



ANALYTICS: SHIFTING PARADIGMS

- Panama papers (2.6 TB, 11.5 billion documents)
  - > 5 billion emails
  - > 3 billion databases
  - > 2 billion PDF documents
  - > 1 billion images
  - > 320,166 text files
  - > 2,242 other files



ANALYTICS: SHIFTING PARADIGMS

Computing

Google Unveils Neural Network with "Superhuman" Ability to Determine the Location of Almost Any Image

Guessing the location of a randomly chosen Street View image is hard, even for well-traveled humans. But Google's latest artificial-intelligence machine manages it with relative ease.

by Emerging Technology from the arXiv
February 24, 2016

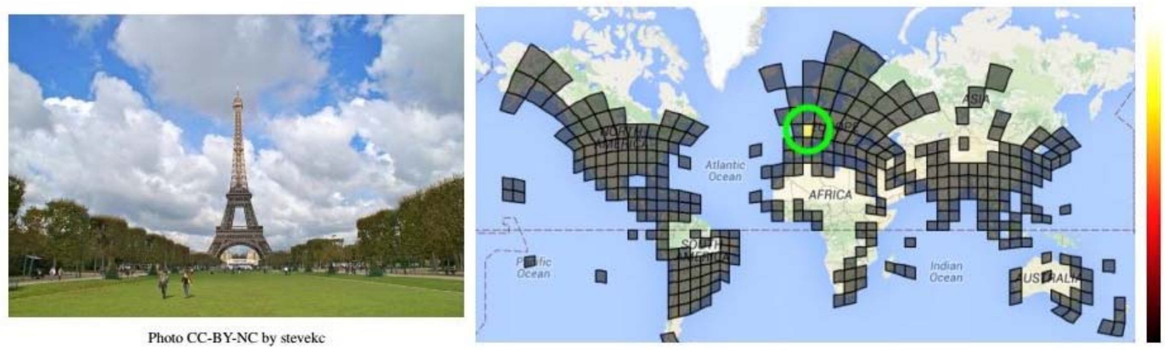


Photo CC-BY-NC by stevekc

(a)

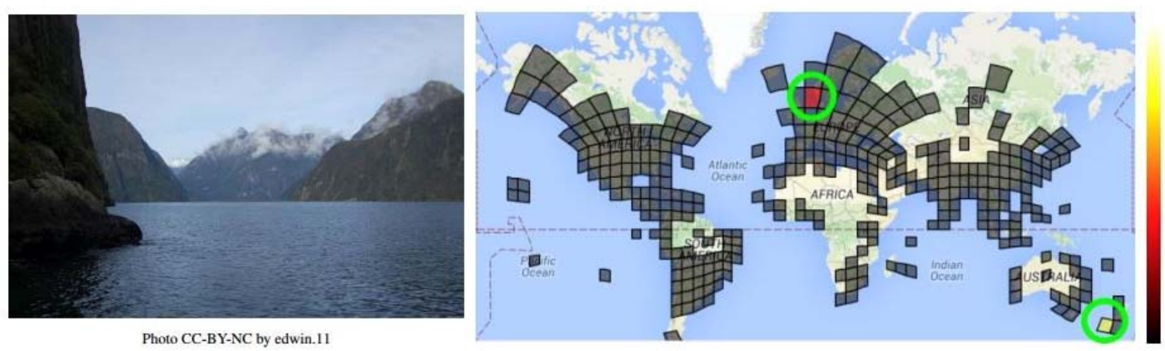
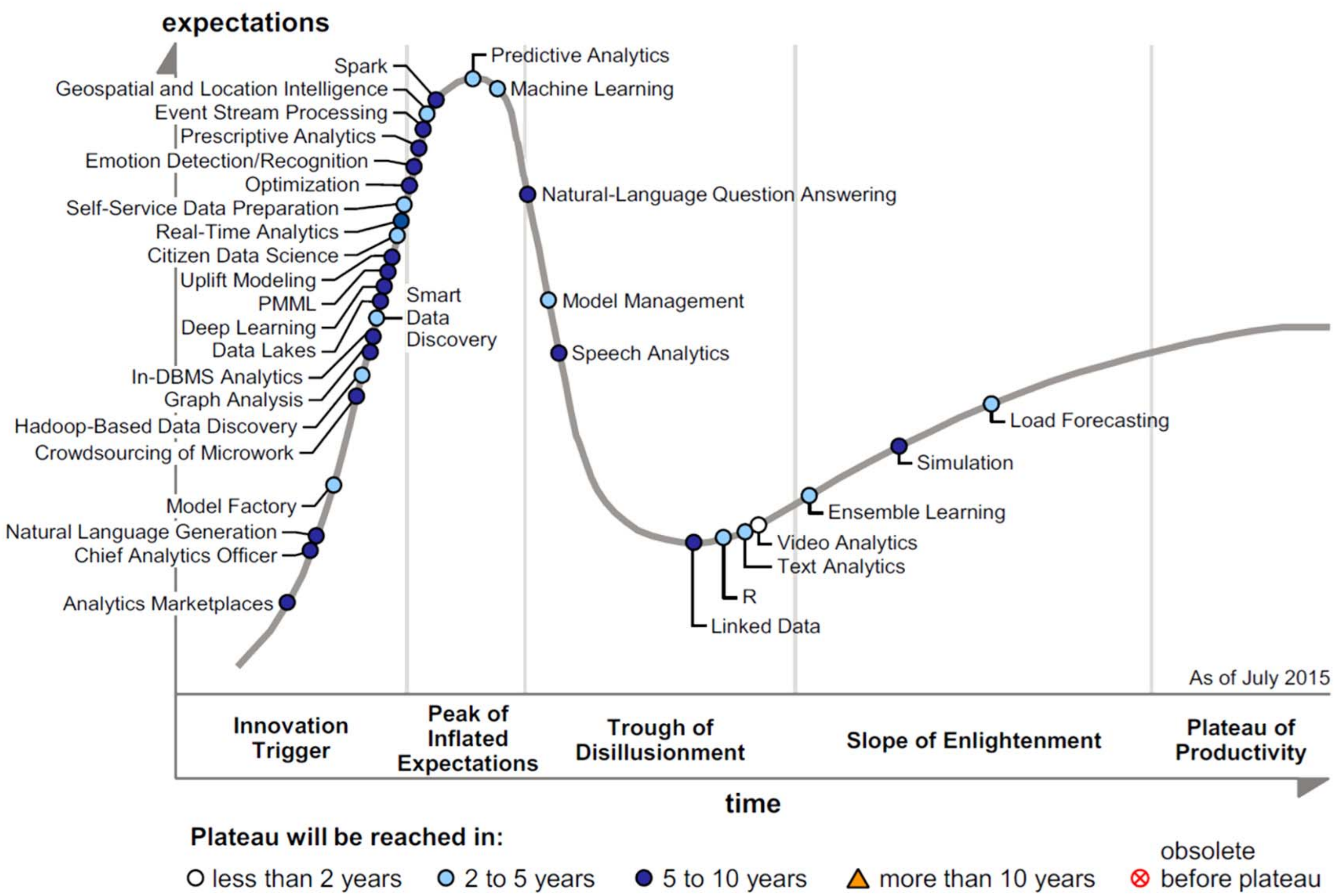


Photo CC-BY-NC by edwin.11

ANALYTICS: SHIFTING PARADIGMS



CASUS: WHO IS INVITED?

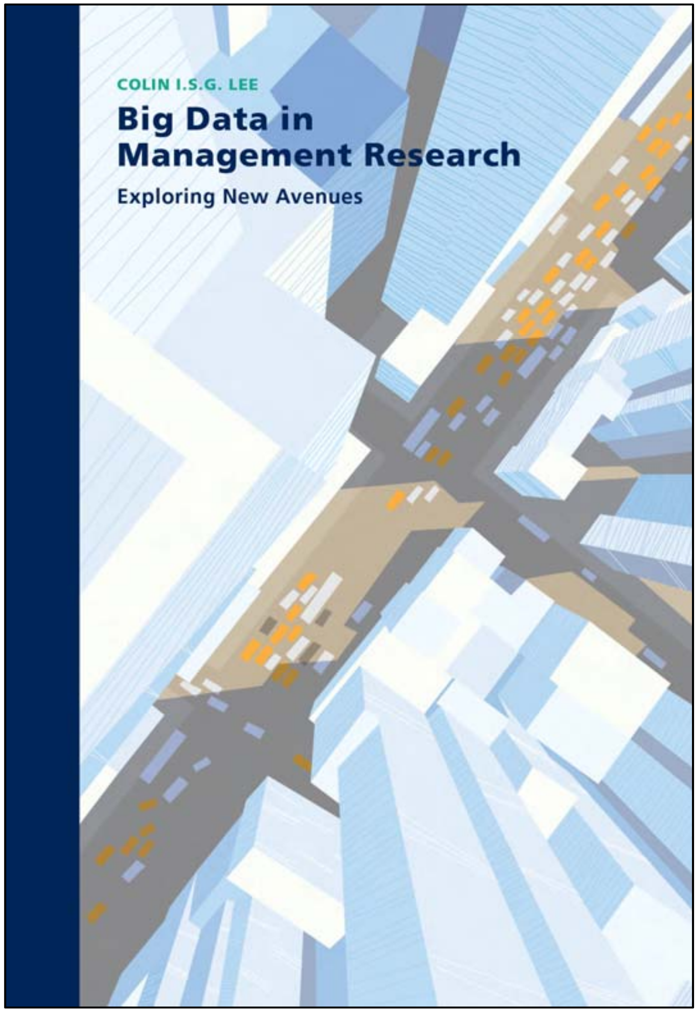
- Applicant tracking data of 48 companies
- 441,769 applicants
- 18 factors:
  - Demographic
  - Biodata
  - Vacancy
  - Candidate
  - Pool of applicants

CASUS: WHO IS INVITED?

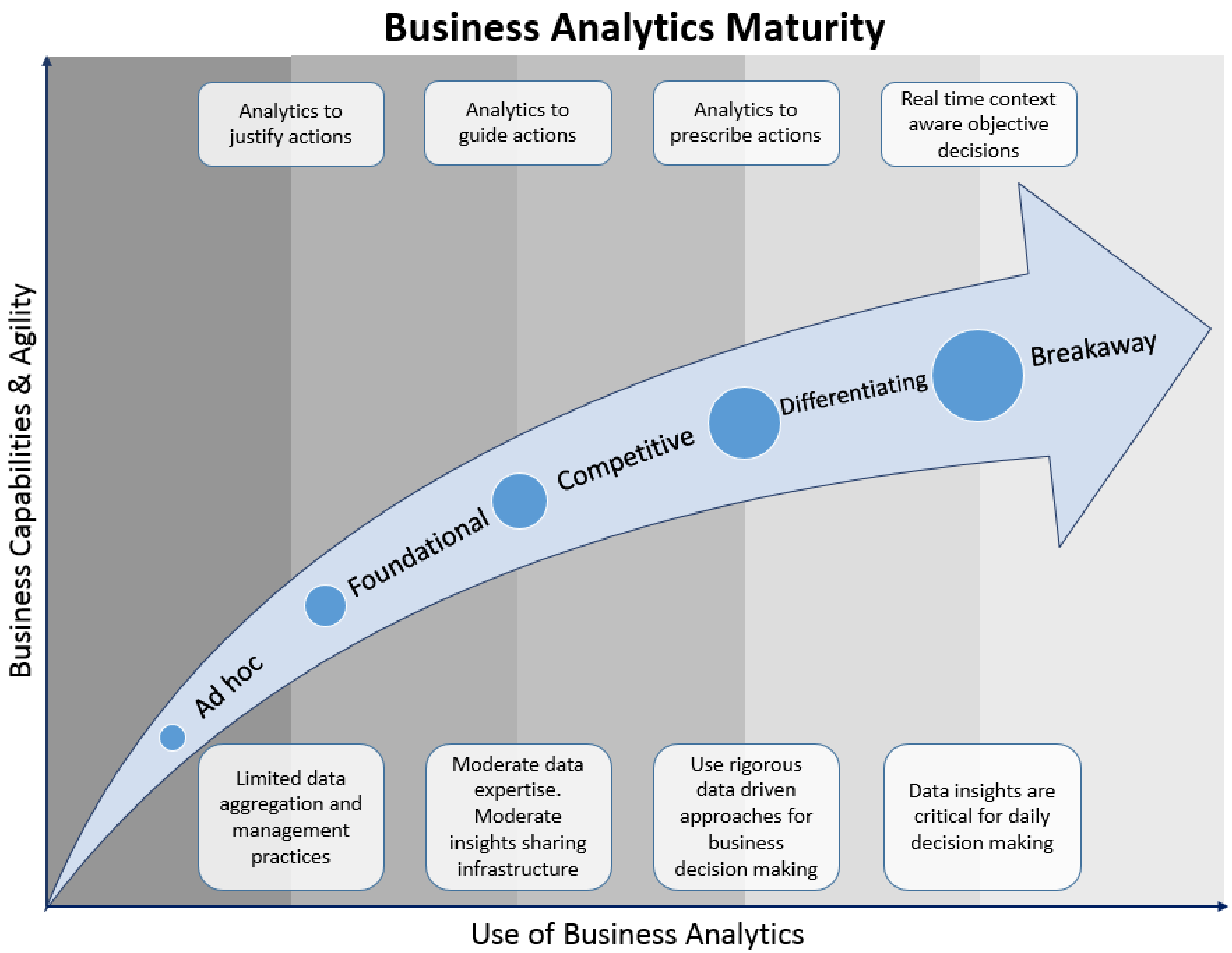
Variable	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1. Invited (1=invited)	.11	.31	-																		
2. Age	36.66	11.91	-.064	-																	
3. Age²	1485.54	931.78	-.07	.99	-																
4. Gender (1=female)	.5	.5	-.024	-.082	-.079	-															
5. Dutch nationality	.66	.47	-.01	-.145	-.138	.052	-														
6. Registered relationship	.26	.44	-.002	.245	.225	-.054	.11	-													
7. Distance from company (in km)[b]	27.05	30.69	-.01	.072	.067	-.16	-.047	.034	-												
8. Experience years	15.1	10.51	-.058	.85	.85	-.091	-.098	.217	.058	-											
9. Experience years²	338.47	411	-.064	.792	.817	-.087	-.09	.181	.054	.959	-										
10. Undereducated	.63	1.36	-.034	.138	.146	-.04	-.021	.03	.003	.138	.141	-									
11. Overeducated	1.1	1.83	.006	-.071	-.069	.062	.007	-.052	-.066	-.069	-.062	-.276	-								
12. Experience relatedness	6.55	2.07	.109	.094	.083	-.033	-.033	.043	.061	.083	.059	-.029	-.053	-							
13. Skill relatedness	7.07	1.09	.075	.069	.058	-.077	-.082	.035	.118	.038	.025	-.024	-.088	.362	-						
14. Education relatedness	6.43	.85	.045	.036	.027	-.071	-.044	.043	.123	.014	.005	-.025	-.106	.274	.404	-					
15. Applied after target reached	.19	.39	.029	-.143	-.132	-.028	.148	-.076	-.008	-.11	-.095	.037	-.001	-.045	-.089	-.092	-				
16. External applicant	.89	.31	-.042	-.001	.005	-.022	.017	-.003	.005	.022	.028	.044	-.087	.005	-.037	.003	.037	-			
17. Number of other applicants[b]	237.59	759.66	-.086	-.089	-.074	.113	.131	-.058	-.035	-.05	-.034	.033	-.033	-.073	-.148	-.113	.322	.194	-		
18. Avg. % of applicants invited by company	.15	.09	.137	.056	.045	-.022	-.222	.024	.115	.036	.027	-.077	-.007	.08	.185	.186	-.239	-.025	-.26	-	
19. Occup. vacancy rate (per 1000)	18.99	10.34	.02	.018	.011	-.06	.008	.026	.06	.011	.003	.012	-.092	.039	.062	.077	.065	-.076	-.013	.031	-

CASUS: WHO IS INVITED?

- Accuracy of approx. 70%.
- When no cover letter is required, accuracy of approx. 80%.
- Age and experience are the most important predictors.
- Results suggest inconsistency in the evaluation of demographic and biodata.



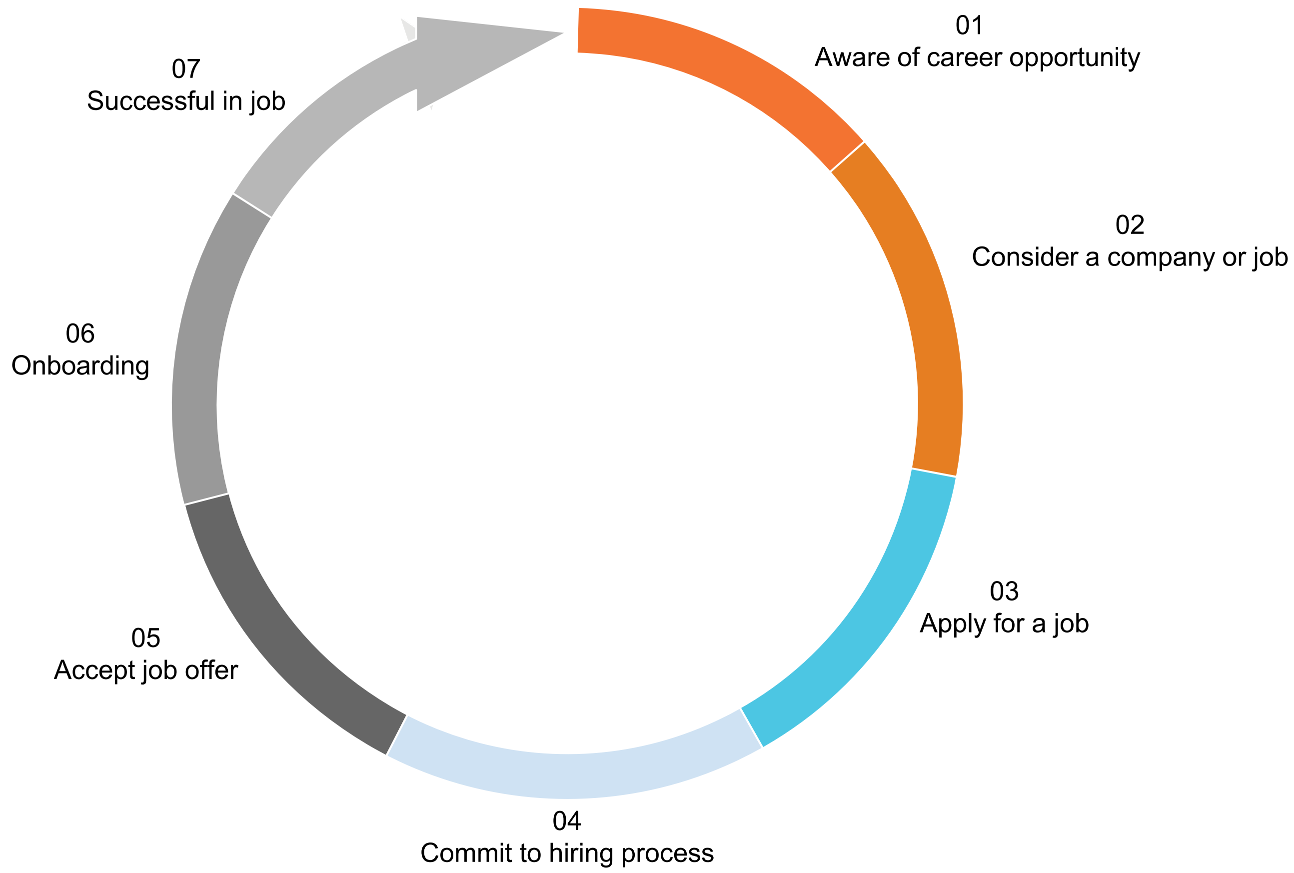
TOWARDS ANALYTICS MATURITY



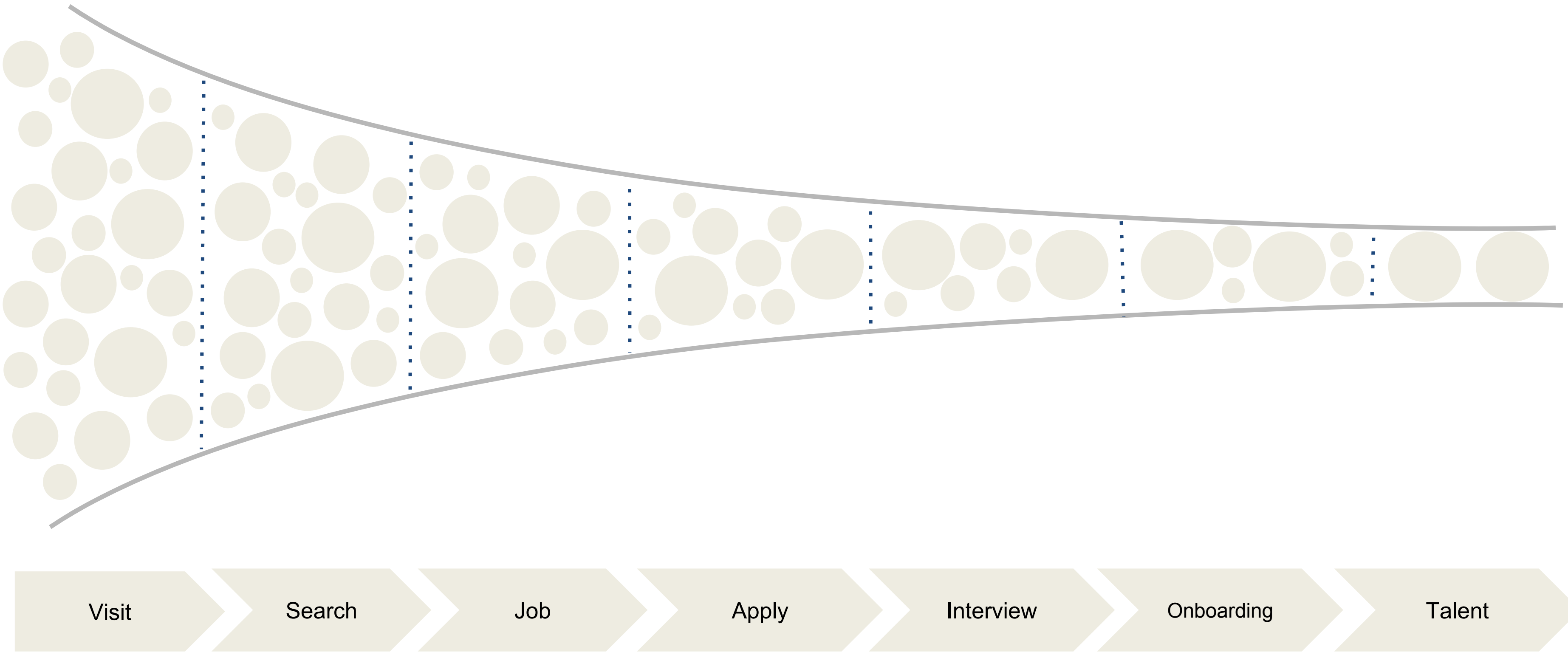
CASUS: THE WHY BEHIND THE HIRE

- Cooperation with Endouble.com

THE APPLICATION JOURNEY



THE RECRUITMENT FUNNEL



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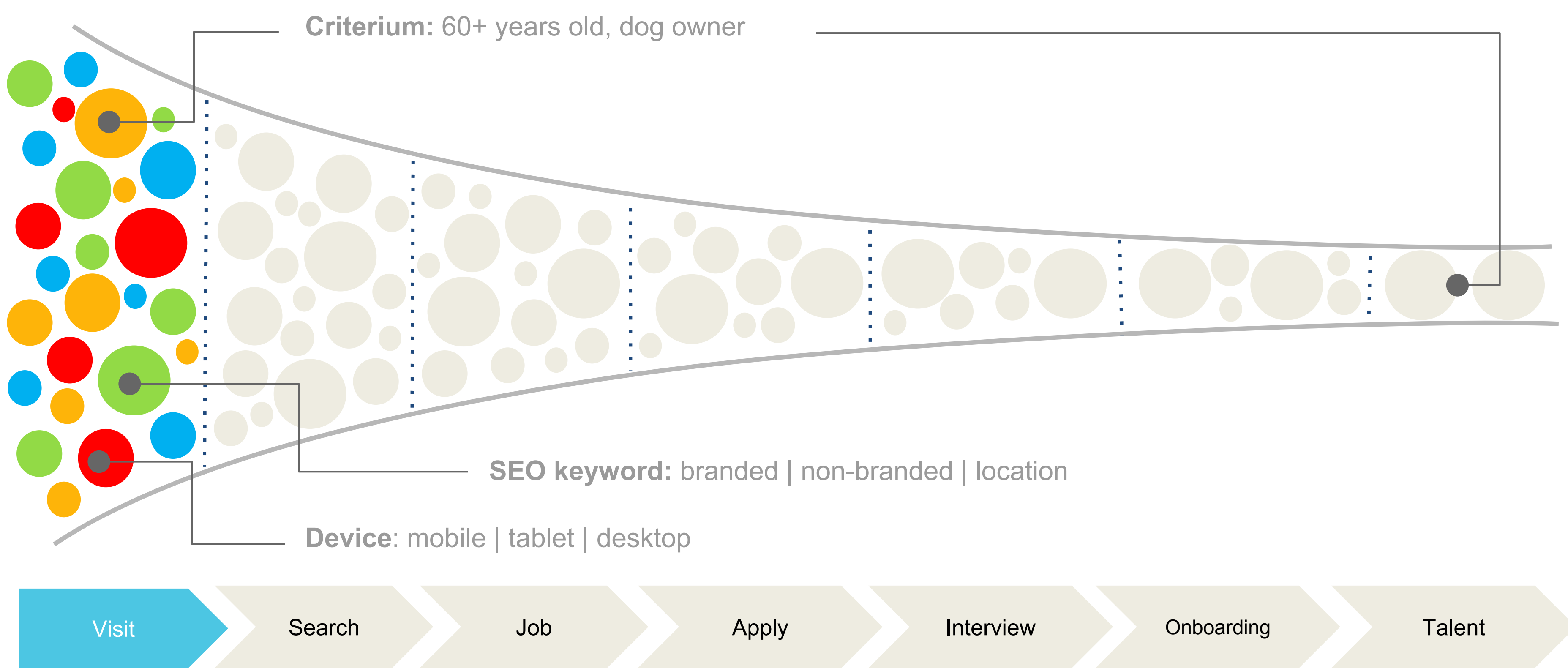

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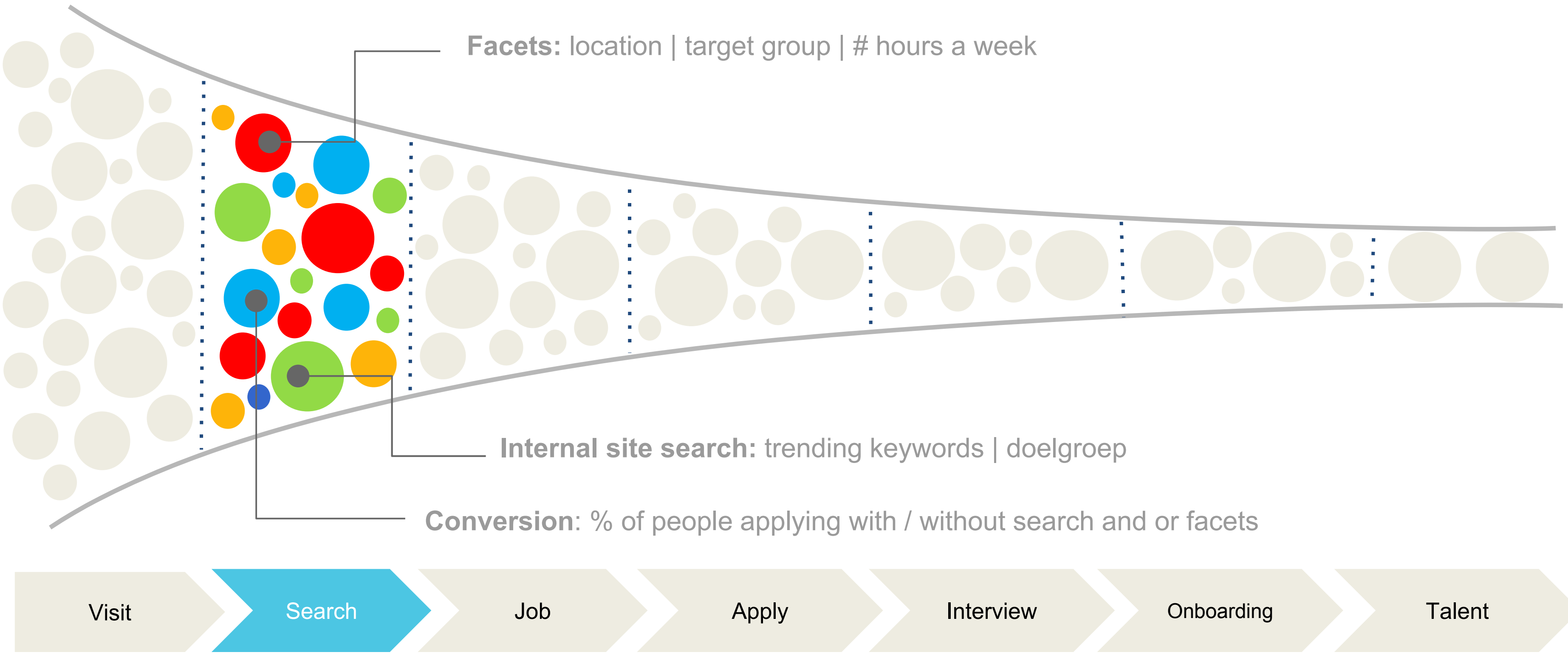

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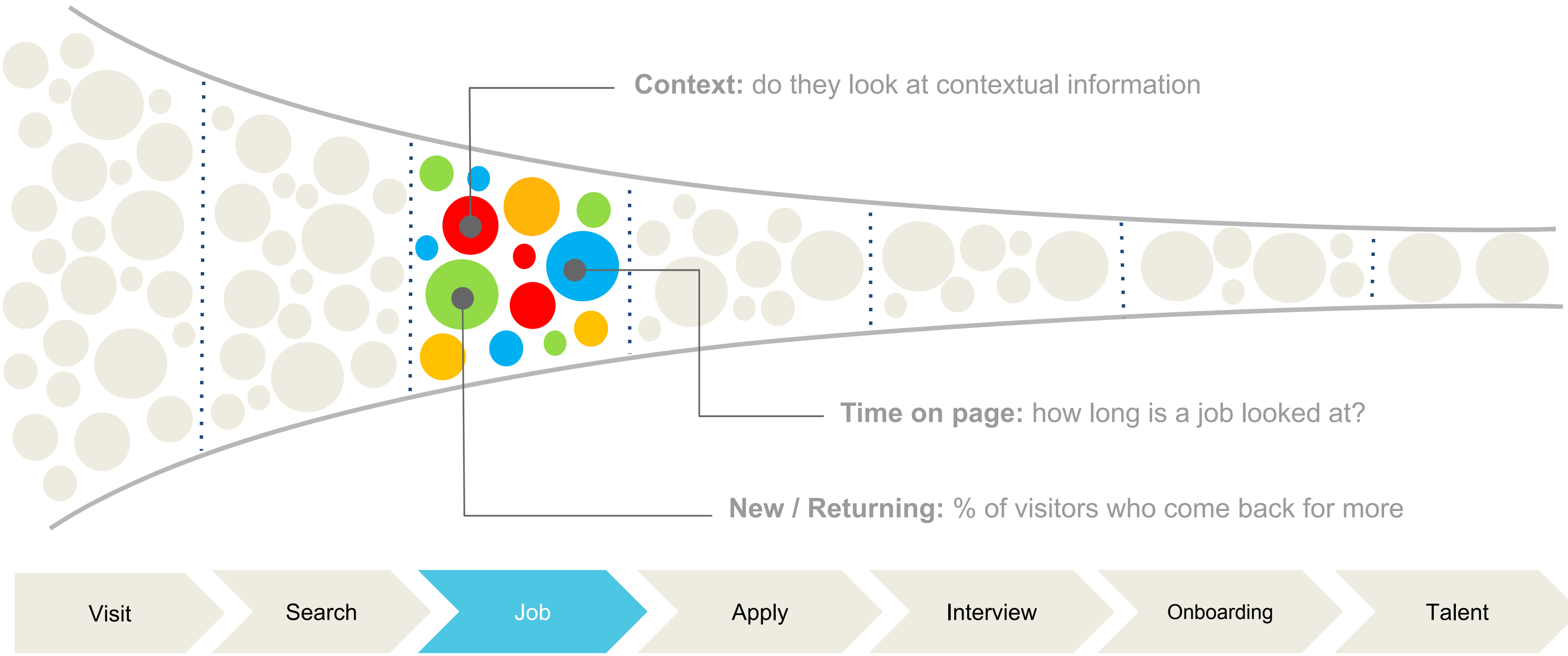

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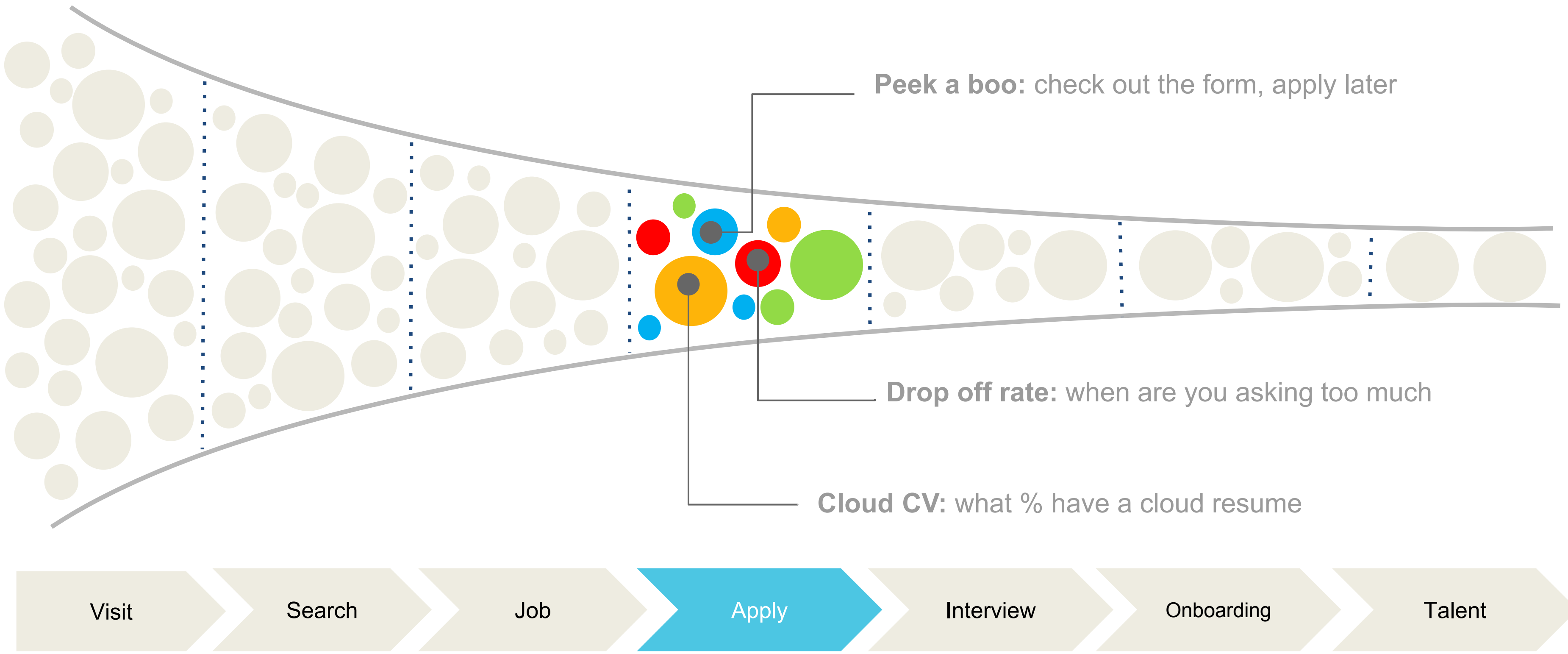

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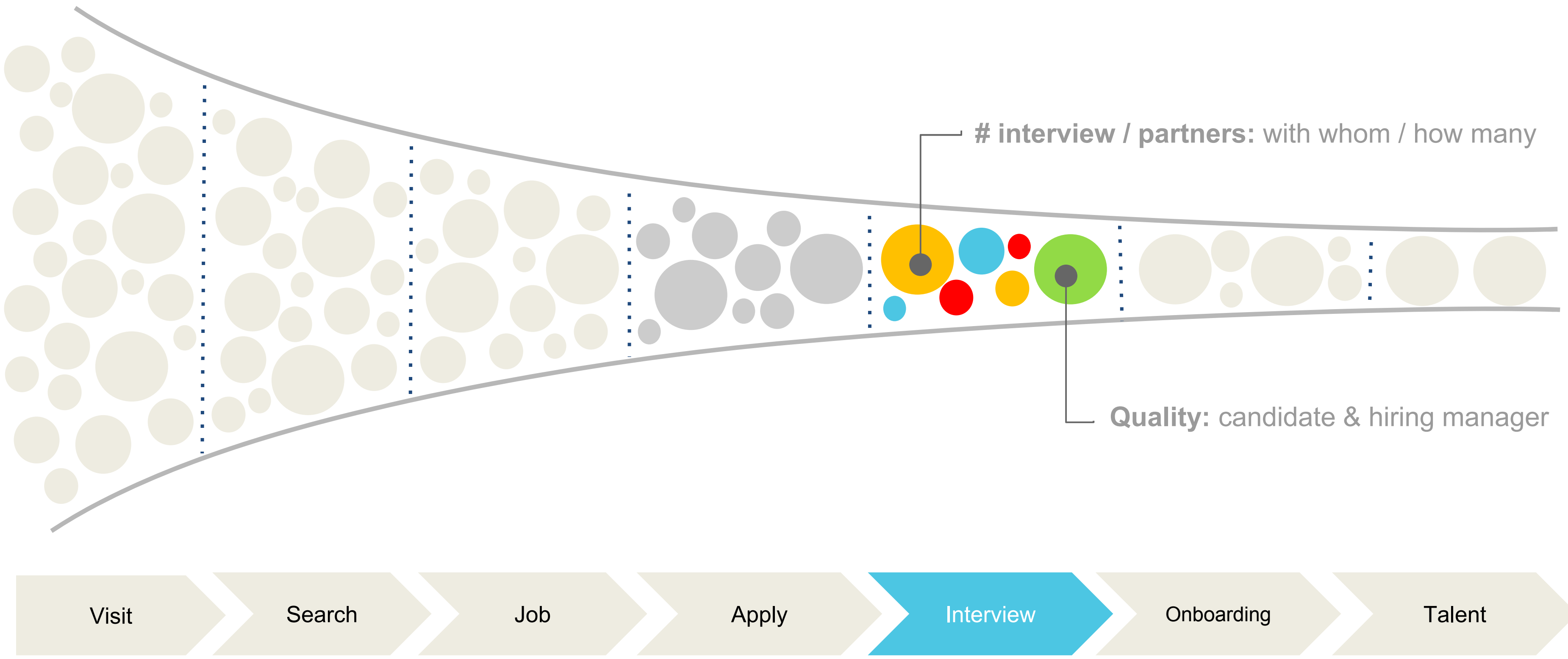

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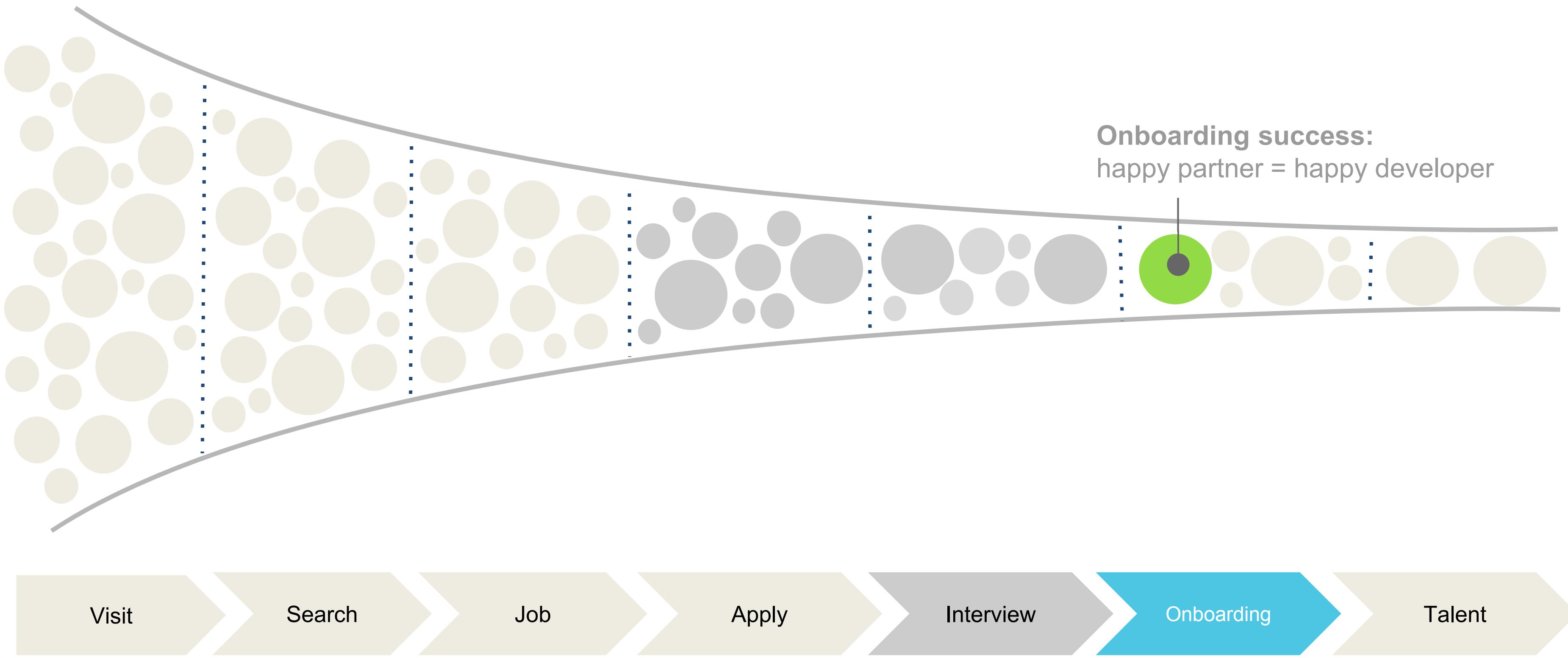

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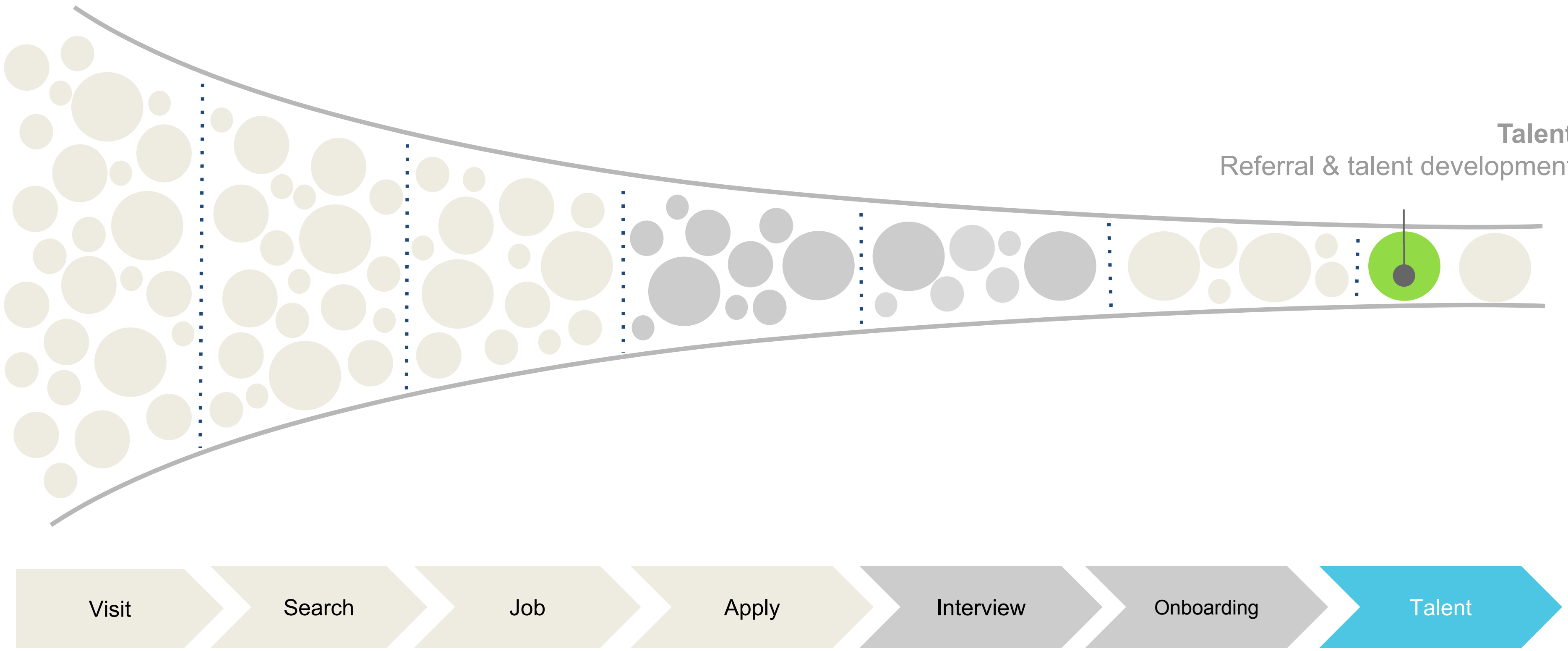

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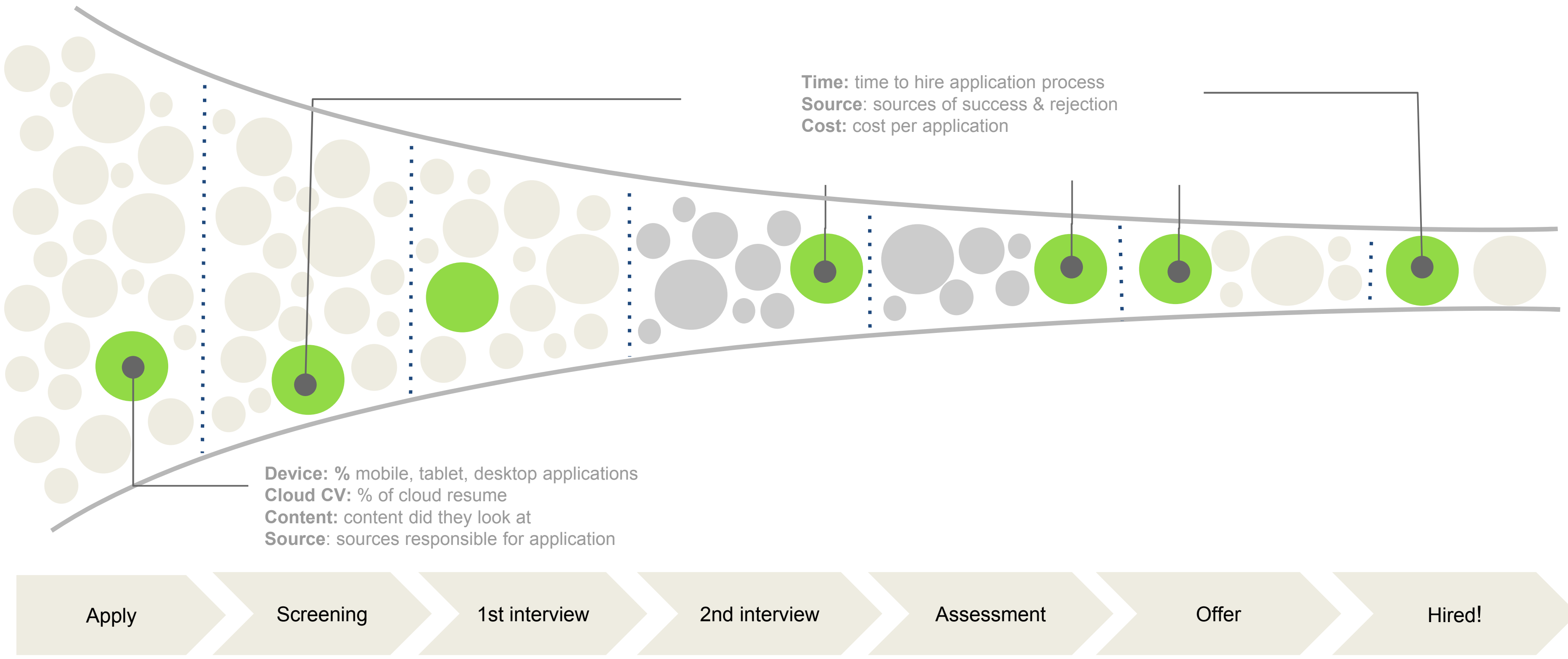

DIVERSITY ANALYTICS

- Diversity: the collective mixture of differences and similarities that includes, for example, individual and organizational characteristics, values, beliefs, experiences, backgrounds, preferences and behaviors.
- Inclusion: the achievement of a work environment in which all individuals are treated fairly and respectfully, have equal access to opportunities and resources, and can contribute fully to the organization's success.

DIVERSITY ANALYTICS

Why is diversity analytics important?

- 1) social case for diversity, whereby employers have a moral obligation to treat employees with fairness and dignity and should ensure that decisions are made without resorting to prejudice and stereotypes.

- 2) diversity allows for the ability to maximize people potential, better understand customers, draw from a wider candidate pool, develop a more positive company image, increase employee engagement, improve retention, innovation and team performance.

DIVERSITY ANALYTICS

DIVERSITY ANALYTICS

Conclusion

- In this organization women are under-represented in senior roles (to a level of certainty that means it pretty much could never happen by chance alone).

DIVERSITY ANALYTICS

Exploring ethnic diversity across teams

- Large financial institute: 29,976 employees with 928 teams
- BAME – Black, Asian, or Minority Ethnic

Comments

- Ethnicity data is often collected on a diversity form completed by employees on joining the organization
- Ethnicity data is rarely mandatory
- The term BAME is primarily used in the UK

DIVERSITY ANALYTICS

DIVERSITY ANALYTICS

Conclusion

- In comparing the Sales and the Professional Service functions, the proportion of BAME staff is significantly lower in Sales than in Professional Service. The average proportion of BAME staff in teams within the Sales is 9.7 percent, and by comparison the average proportion of BAME staff in teams within Professional Service function is 14.39 percent.

DIVERSITY ANALYTICS

Conclusion

- In comparing the Sales and the Professional Service functions, the proportion of male staff is significantly higher in Sales than in Professional Service groups within our organization. The average percentage of male staff in teams within Sales is 71.26 percent, and by comparison the average proportion of male staff in teams within the Professional Service function is 44.4 percent.

DIVERSITY ANALYTICS

DIVERSITY ANALYTICS

Conclusion

- We have a significantly higher proportion of BAME in our teams within the “Professional Service” functions as compared to “Sales” teams even when we take into account that the diversity levels tend to be much higher in our London teams than our outside London teams.

TURNOVER ANALYTICS

- Employee turnover: all leavers of an organization, including those who resign, are made redundant, take retirement, or exit the organization for any other reason.
- The cost of employee turnover can be substantial and has been projected at 93-200 percent of each single leaver's salary depending on the skill, level of responsibility and the difficulty to replace.

TURNOVER ANALYTICS

TURNOVER ANALYTICS

Conclusion

- Even though the descriptive report suggested quite large differences between countries in terms of turnover rates, the chi-square analysis confirmed there was no significant difference between what you would expect to see in each country (given its size) and what was observed.

TURNOVER ANALYTICS

TURNOVER ANALYTICS

Conclusion

- We can now deduce that the impact that “country” has on both “Survey Engagement” and “Team Turnover” within our ANOVA (and Welch) is mainly due to how different Spain is compared to the other countries in our data set.

  We can say that Spain has significantly lower engagement than all other countries based on the survey engagement values, and significantly higher turnover than both the UK and the United States.

TURNOVER ANALYTICS

TURNOVER ANALYTICS

Conclusion

- Country differences do not come out as significant in accounting for turnover. However, women are more than twice as likely to leave as men and a higher appraisal rating will increase the chances of employees staying (thus women who get a low performance rating are a ‘higher risk of leaving’ category than other employees).

TURNOVER ANALYTICS

TURNOVER ANALYTICS

Conclusion

- When you take into account the various country effects in the model alongside the survey measures, it seems that the country differences no longer come out as being as important in predicting team turnover as much as levels of engagement and perceptions of the team experiences of the company's 'drive for performance' culture.

VU

QUESTIONS