M2009

12th Annual Data Mining Conference

TeliaSonera

12th Annual Data Mining Conference

Experiences on Experiment Design in Direct Marketing

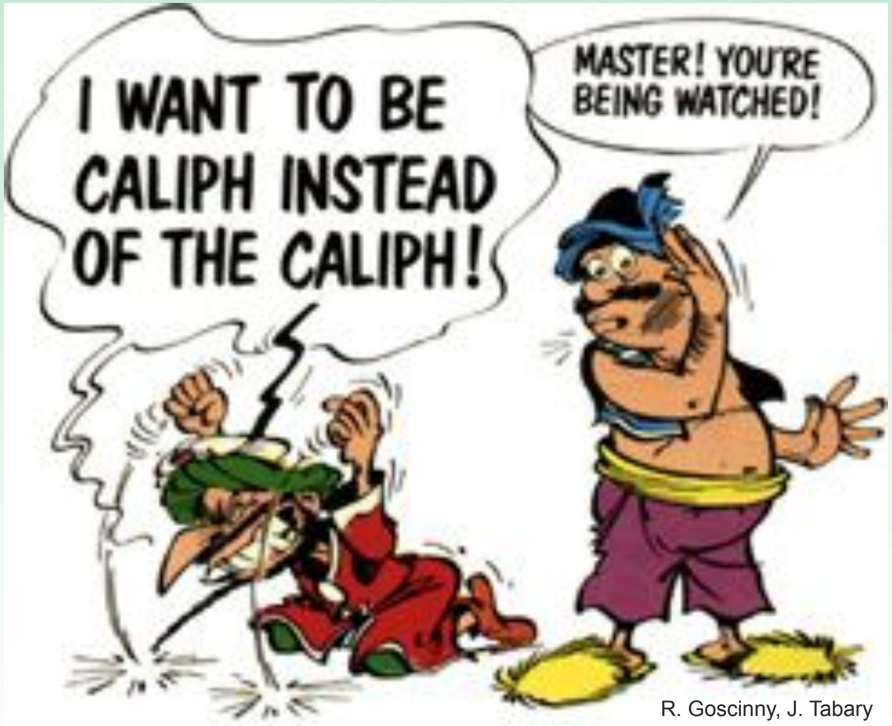
Riku Mäkeläinen, TeliaSonera Sverige AB

Contents

- Background
- Basic idea behind designed experiments
- Concrete case
- Experiences and business benefits
- Summary

Measure the “hard to measure” things

What works and what doesn’t work?
How to reach the goal efficiently?!



R. Goscinny, J. Tabary

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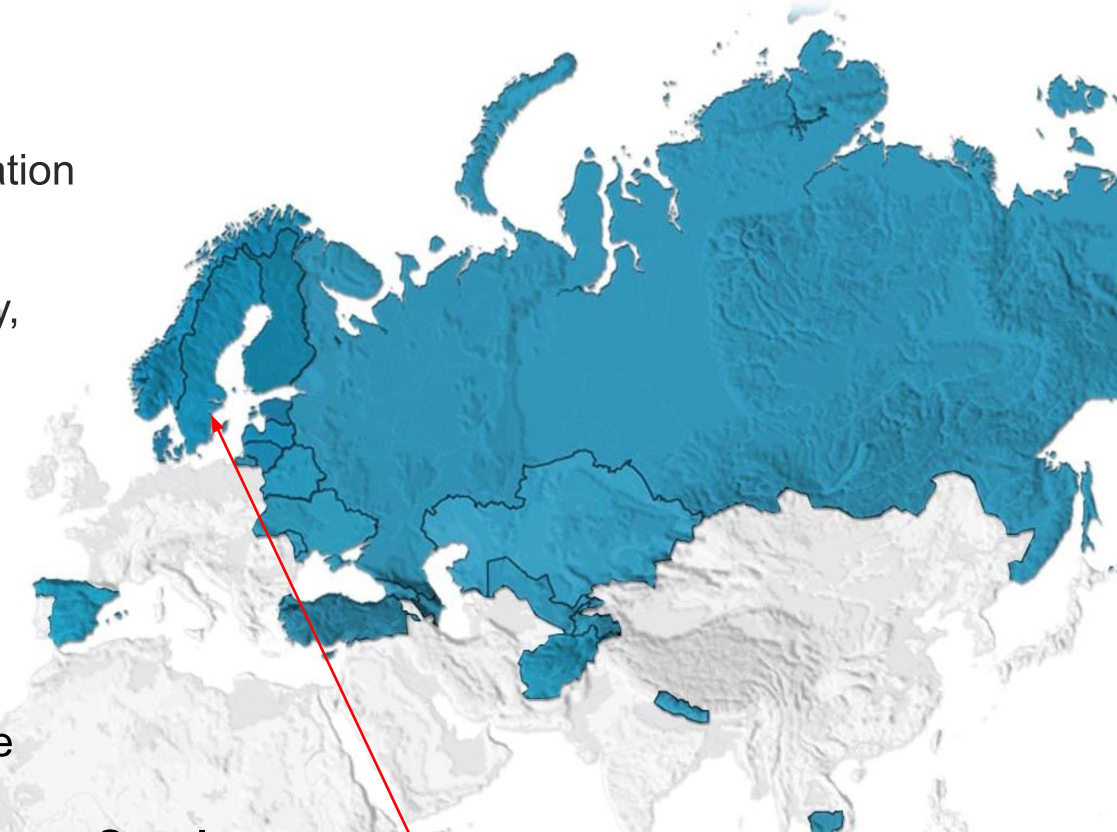
- TeliaSonera provides telecommunication services in the Nordic and Baltic countries, the emerging markets of Eurasia, including Russia and Turkey, and in Spain
- Head office in Stockholm, Sweden
- Total number of subscriptions 137 million (2009Q1)
- 2008 net sales SEK 103 585 million
- Approx. 32 000 employees
- Largest shareholders - Swedish state (37.3%) and Finnish state (13.7%)
- http://www.teliasonera.com



Sweden
- Broadband subscriptions 1 132 000
- Fixed subscriptions 3 906 000
- IPTV subscriptions 333 000
- Mobile subscriptions 5 412 000

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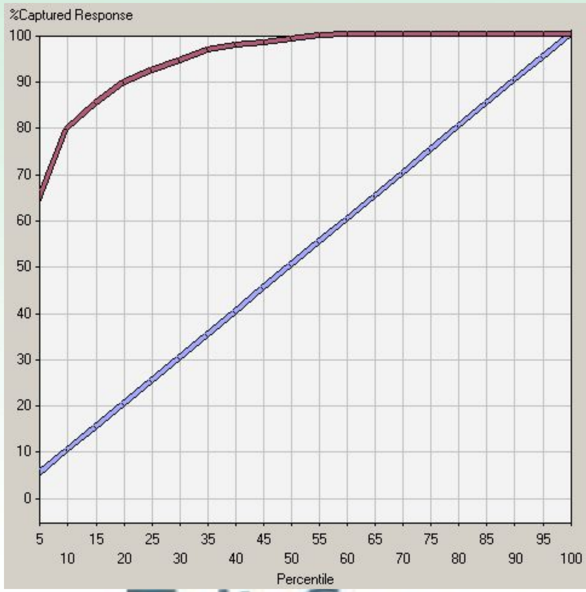
Why Did TeliaSonera Sverige Broadband Decide to Implement DOE

- Plenty of experiences with score models and database analyses, however
  - Score models can not fully address variations in material and offers
  - Something was missing, process should be improved
- Stronger demand to measure results and use control groups
  - Try to measure the 'hard to measure' things
- Need for improved control over marketing activities
- Reduced marketing budgets



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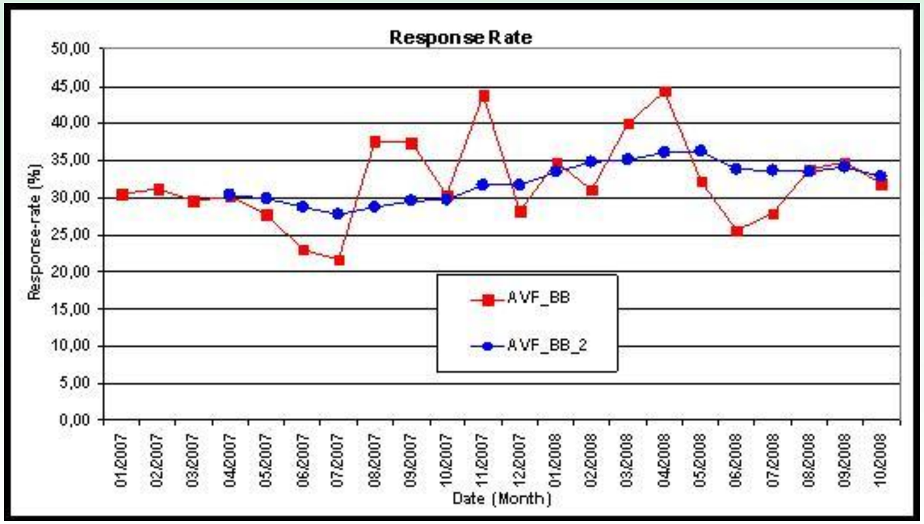
Implicit Goals

- Learn how to improve response rate
- Learn how to reduce variation in response rate
- Learn how to make campaign process robust, e.g. less sensitive to uncontrollable changes in process
- Learn which variables are important to control and which are not
- Learn how to increase ROI



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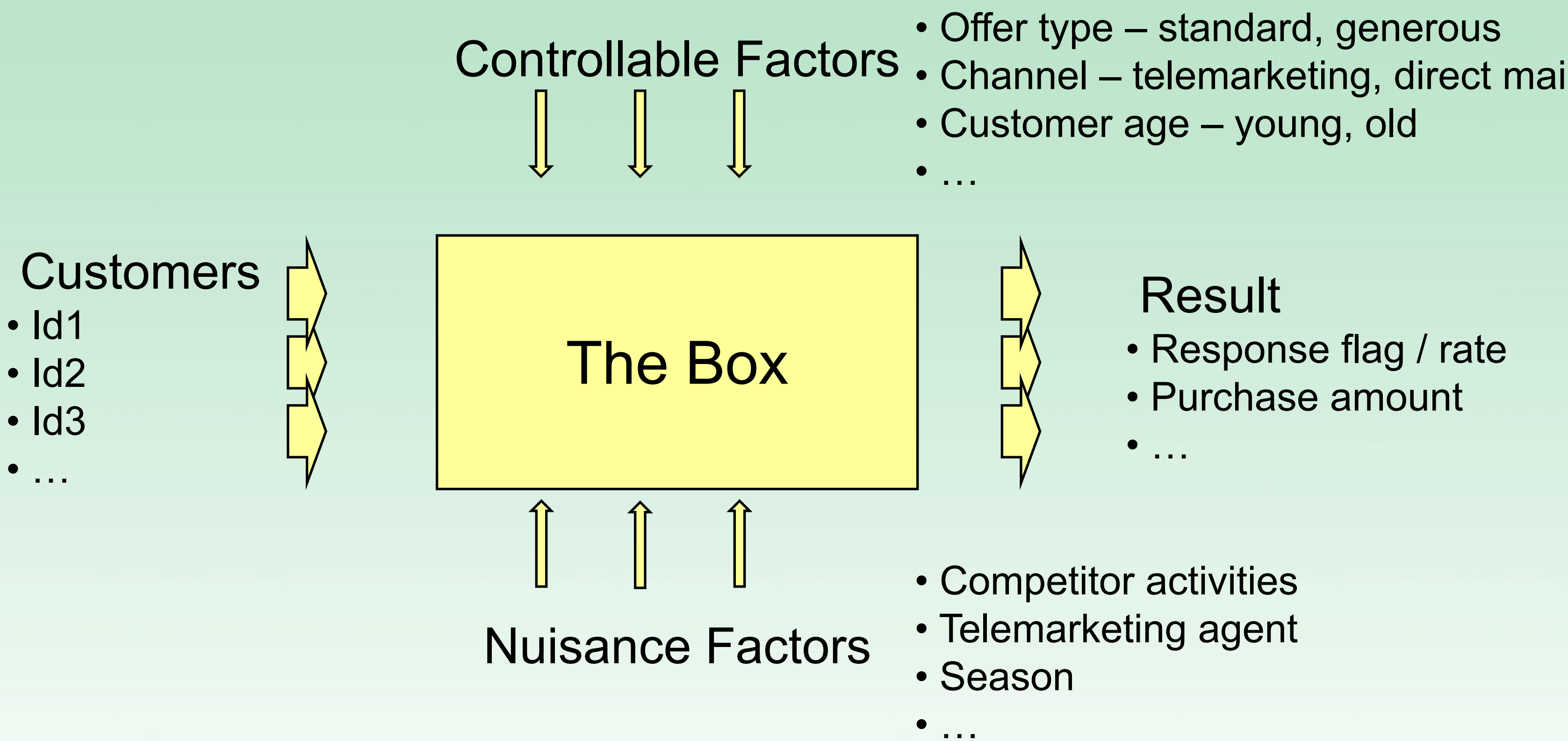
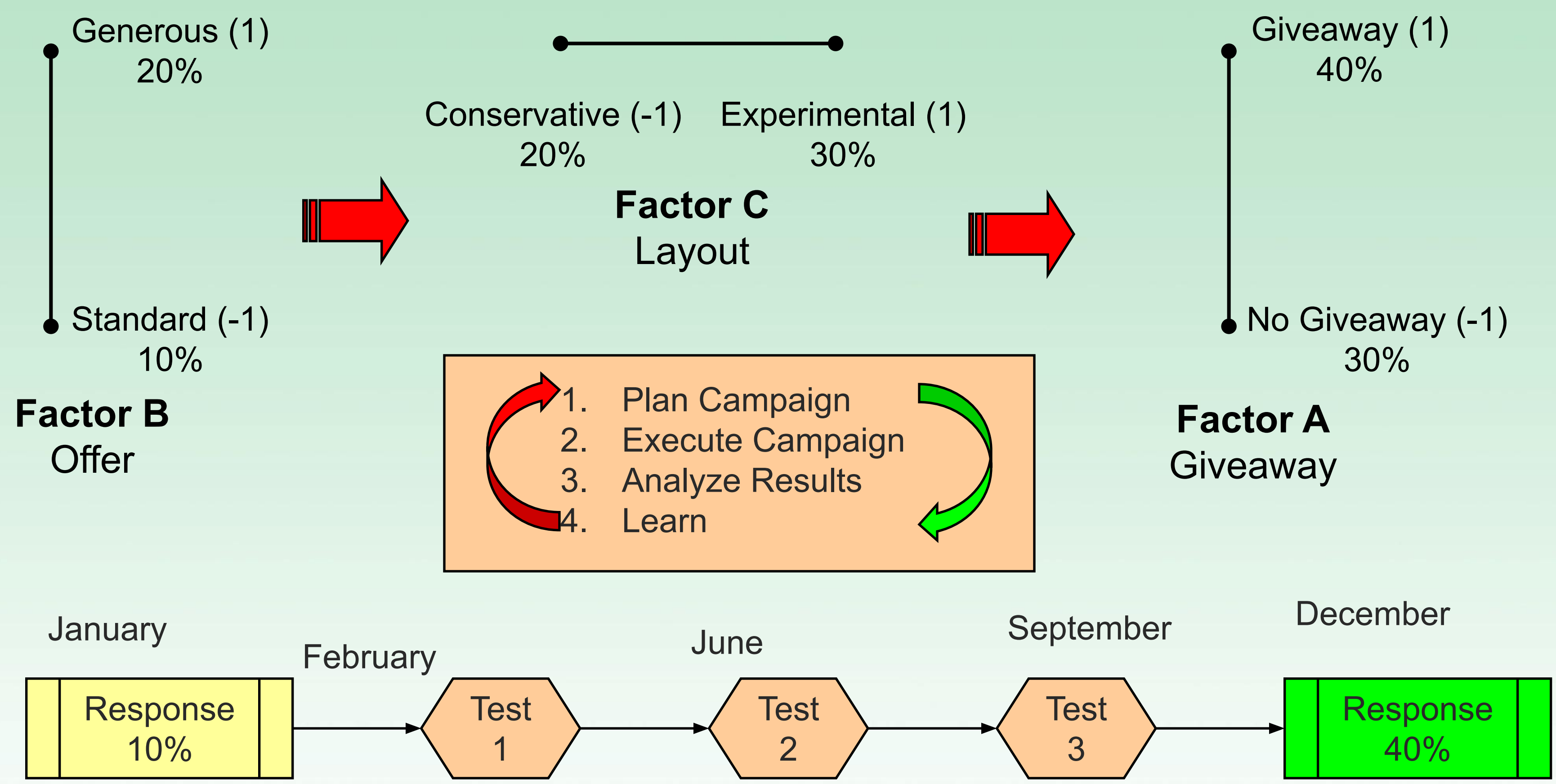
Basic Idea Behind Experiment Design



- General idea: show significance of effect of given factor to response variable
- Run: particular experiment with each factor at specific level – communication

  example: communication 1: layout 1 + DVD-player + apartment => 5% response
  communication 2: layout 2 + DVD-player + apartment => 7 response%

One, Two, Three…



- Thanks to diligent testing, response rate goes from 10% to 40% - well done!
- Or…?

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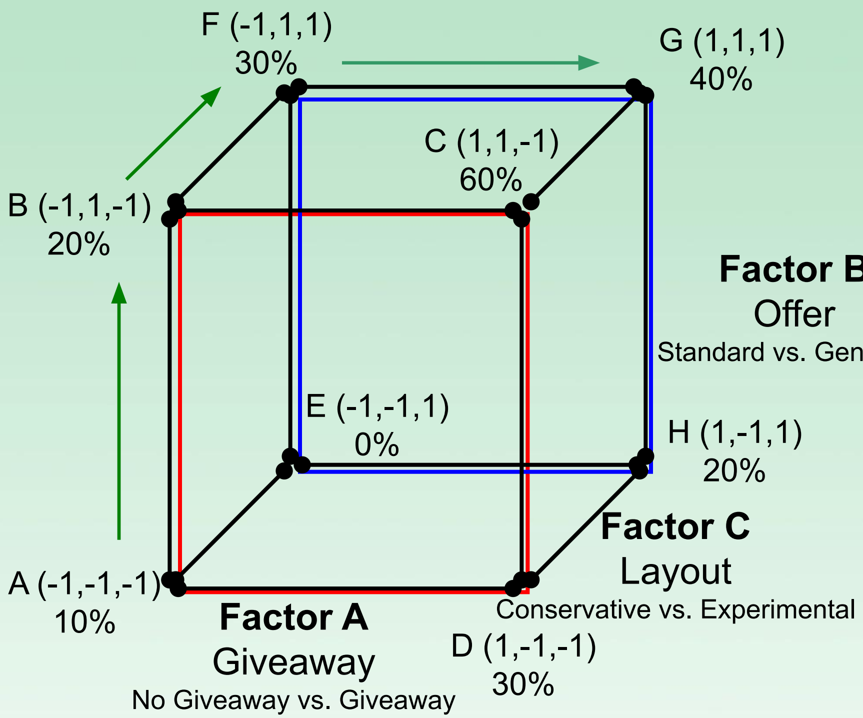
Traditional 'Test One-Factor-at-a-Time' Inefficient



Optimal

Suboptimal

Run	Factor A	Factor B	Factor C	Result
1	-1	-1	-1	10%
2	1	-1	-1	30%
3	-1	1	-1	20%
4	1	1	-1	60%
5	-1	-1	1	0%
6	1	-1	1	20%
7	-1	1	1	30%
8	1	1	1	40%

Effect of Layout = (E + F + G + H – A – B – C – D) / 4
= –7,5%

- It's much more efficient to test several factors simultaneously than testing one factor at a time
- With only one factor at time
  - many more runs needed
  - interactions can't be estimated
  - may lead to suboptimal result

wasting resources and providing little understanding

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Many, Many Factors…

- Number of factors can easily explode:
  - Offer A / Offer B
  - Layout A / Layout B
  - Giveaway / No Giveaway
  - Channel A / Channel B
  - Offensive Dialogue / Defensive Dialogue
  - House / Apartment
  - City / Countryside
  - Male / Female
  - Younger / Older
  - Family / No Family
  - Lower Income / Higher Income
  - Heavy-user / Low-user
  - Telemarketing Agency A / Telemarketing Agency B
  - Contact During Peak Time / Contact During Off-Peak Time
  - …
- Add 2 more age groups, 2 more income categories, 2 more family status, …

… Results in Many, Many, Many Runs

- With relatively few factors the number of target groups explodes
  - with 2 factors we get 2^2 = 4 target groups
  - with 5 factors we get 2^5 = 32 target groups
  - with 10 factors we get 2^10 = 1024 target groups
  - with 16 factors we get 2^16 = 65536 target groups
- Practical problems to export and manage so many communication groups
- Solution: fractional factorial designs

=> We can test several campaign components in just one campaign with relatively few communications

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Fractional Factorial Designs

- Reduces number of runs needed but sacrifices analysis possibilities
- We can still analyze main effects and certain interactions
- We can not analyze all interactions, but often important ones
- Often practical since interactions between 3-4 or more factors are unlikely
- Afterwards fractional design can be completed to full design
- Orthogonal: effects of any factor sum out to zero across the effects of other factors
- Example: 3 factors
  - Full factorial needs 8 runs
  - ½ fractional needs only 4 runs
  - Resolution 3
  - Confounding Factor C = Factor A * Factor B
  - Aliasing:
    - Factor A + Factor B * Factor C
    - Factor B + Factor A * Factor C
    - Factor C + Factor A * Factor B

Run	Factor A	Factor B	Factor C
1	-1	-1	-1
2	1	-1	-1
3	-1	1	-1
4	1	1	-1
5	-1	-1	1
6	1	-1	1
7	-1	1	1
8	1	1	1

Full Factorial

Run	Factor A	Factor B	Factor C
1	-1	-1	1
2	1	-1	-1
3	-1	1	-1
4	1	1	1

½ Fractional

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Other Related Things

- **Plan carefully and randomize**
- Control natural blocks – maybe seasonality
- Check nonlinearities – customer base might not behave linearly
- Think what interactions are probably not important – alias
- Choose factor levels carefully – not too close or too far away
- Think about multiple comparison problem – however, be liberal
- Pay attention to ‘impossible’ combinations – advanced designs
- Consider if your factors are fixed as usual or if some are random
  - Fixed: gender is male or female
  - Random: city
  - Mixed Modeling

Sample Size

- Before executing test we should have some idea how many respondents we can have and how many we need
- And have an idea what we really want to measure (= how big a difference is really a difference)
- Target group size depends on
  - Expected response rate
  - How big a difference we will observe
  - How certain we want to be to find the difference if it exists

Example: to have 90% probability of detecting a departure of 3%-unit from base response-% of 34,5% (with 0.05 significance)
⇒ we need 10 756 customers
(with 300 + 300 probability would be <12%)

```
proc power;
  twosamplefreq
  refproportion = 0.345
  proportiondiff = 0.03
  ntotal = .
  power = 0.9;
run;
```

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Design, Execution and Analysis Tools

- Microsoft Excel – simple and powerful and often more than good enough!
- SAS STAT, SAS GRAPH & SAS QC / ADX
- SAS Enterprise Miner
- SAS Campaign Studio

- **Execute test as planned!**

Analysis Results After Experiment

Assuming test runs were executed as planned…

- We know which factors are important and which are not important
  - How much a factor increases / decreases response
  - Possibly we also know important factor combinations (interaction => $$$)
  - Quantitatively
- Or we know direction where we should continue investigation
- We have equation for response

  => we can extrapolate results to all combinations, even to ones not tested
- And we have done this efficiently with relatively few runs
  - No resources wasted
- Important to also analyze if highest response rate gives best ROI

Estimation

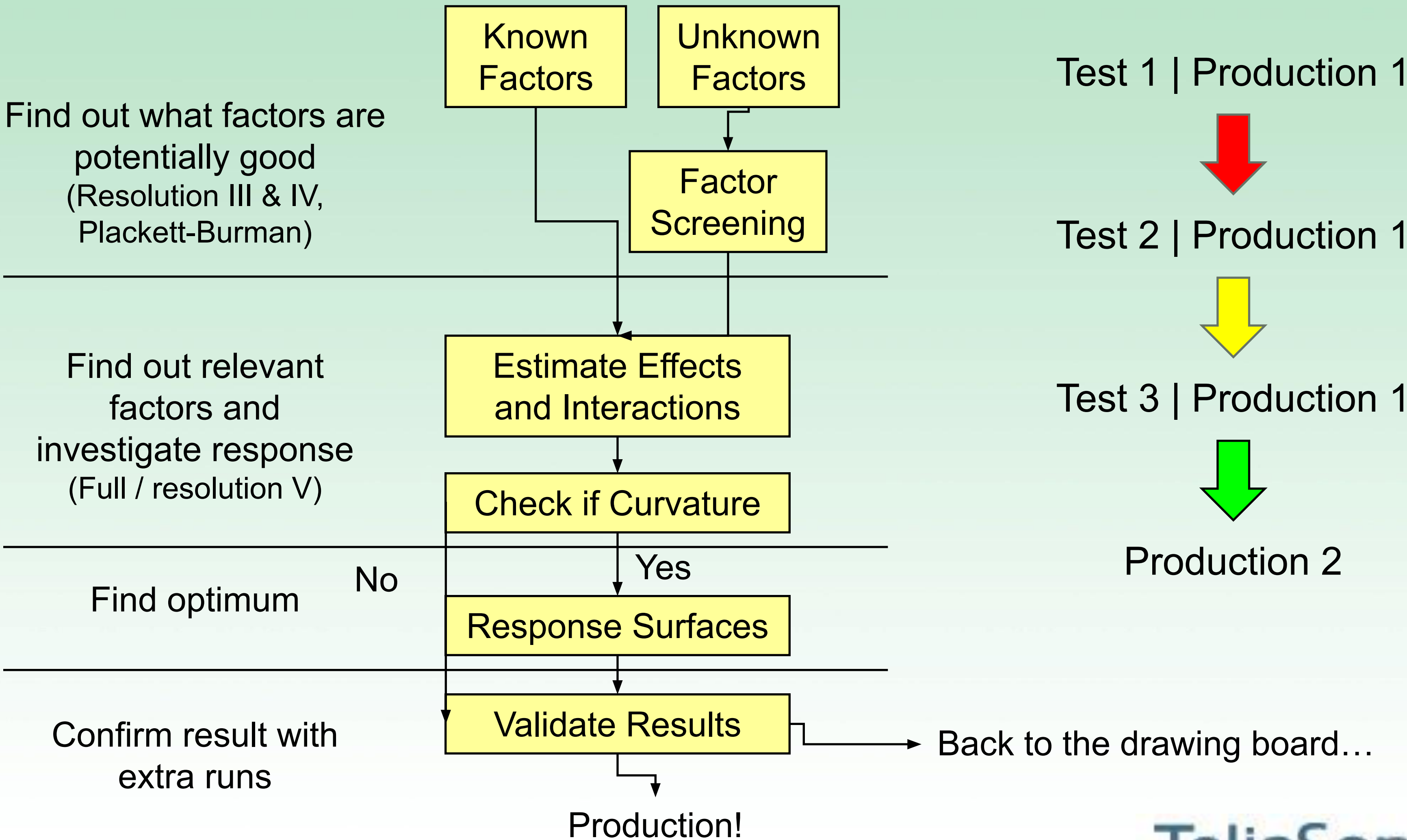
- We can extrapolate results to all combinations, even to ones not tested

TEST				
Offer	1	1	2	2
Giveaway	1	2	1	2
Layout 1	14%			40%
Layout 2		9%	13%	
Layout 3		6%	10%	
Layout 4	1%			7%

We execute 8 communications but get results from 16 (and even more by counting interactions)

MODELED RESULT				
Offer	1	1	2	2
Giveaway	1	2	1	2
Layout 1	14%	23%	28%	42%
Layout 2	7%	12%	15%	24%
Layout 3	3%	6%	7%	12%
Layout 4	1%	3%	3%	6%

Process – Important to Get it Right!



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Case 1: Win Back Fix

- Aim: win back fixed line traffic, January 2008
- Test: how five factors affect response
- Full factorial design => $2^5 = 32$ runs

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Campaign Results

- Average 10,54%

RUN	F_TELIA	F_NIX	F_3	F_4	F_5	RESPRATE
1	TELIA_NO	NIX_NO	low	low	low	11,72
2	TELIA_YES	NIX_NO	low	low	low	12,48
3	TELIA_NO	NIX_YES	low	low	low	10,74
4	TELIA_YES	NIX_YES	low	low	low	14,83
5	TELIA_NO	NIX_NO	high	low	low	9,34
6	TELIA_YES	NIX_NO	high	low	low	8,14
7	TELIA_NO	NIX_YES	high	low	low	10,28
8	TELIA_YES	NIX_YES	high	low	low	15,50
9	TELIA_NO	NIX_NO	low	high	low	11,70
10	TELIA_YES	NIX_NO	low	high	low	12,50
11	TELIA_NO	NIX_YES	low	high	low	10,37
12	TELIA_YES	NIX_YES	low	high	low	12,48
13	TELIA_NO	NIX_NO	high	high	low	8,51
14	TELIA_YES	NIX_NO	high	high	low	7,17
15	TELIA_NO	NIX_YES	high	high	low	8,74
16	TELIA_YES	NIX_YES	high	high	low	7,44
17	TELIA_NO	NIX_NO	low	low	high	12,12
18	TELIA_YES	NIX_NO	low	low	high	13,68
19	TELIA_NO	NIX_YES	low	low	high	14,73
20	TELIA_YES	NIX_YES	low	low	high	13,88
21	TELIA_NO	NIX_NO	high	low	high	10,25
22	TELIA_YES	NIX_NO	high	low	high	9,20
23	TELIA_NO	NIX_YES	high	low	high	11,96
24	TELIA_YES	NIX_YES	high	low	high	14,73
25	TELIA_NO	NIX_NO	low	high	high	8,26
26	TELIA_YES	NIX_NO	low	high	high	9,41
27	TELIA_NO	NIX_YES	low	high	high	8,67
28	TELIA_YES	NIX_YES	low	high	high	7,26
29	TELIA_NO	NIX_NO	high	high	high	7,11
30	TELIA_YES	NIX_NO	high	high	high	8,00
31	TELIA_NO	NIX_YES	high	high	high	6,51
32	TELIA_YES	NIX_YES	high	high	high	9,52
					AVG	10,54

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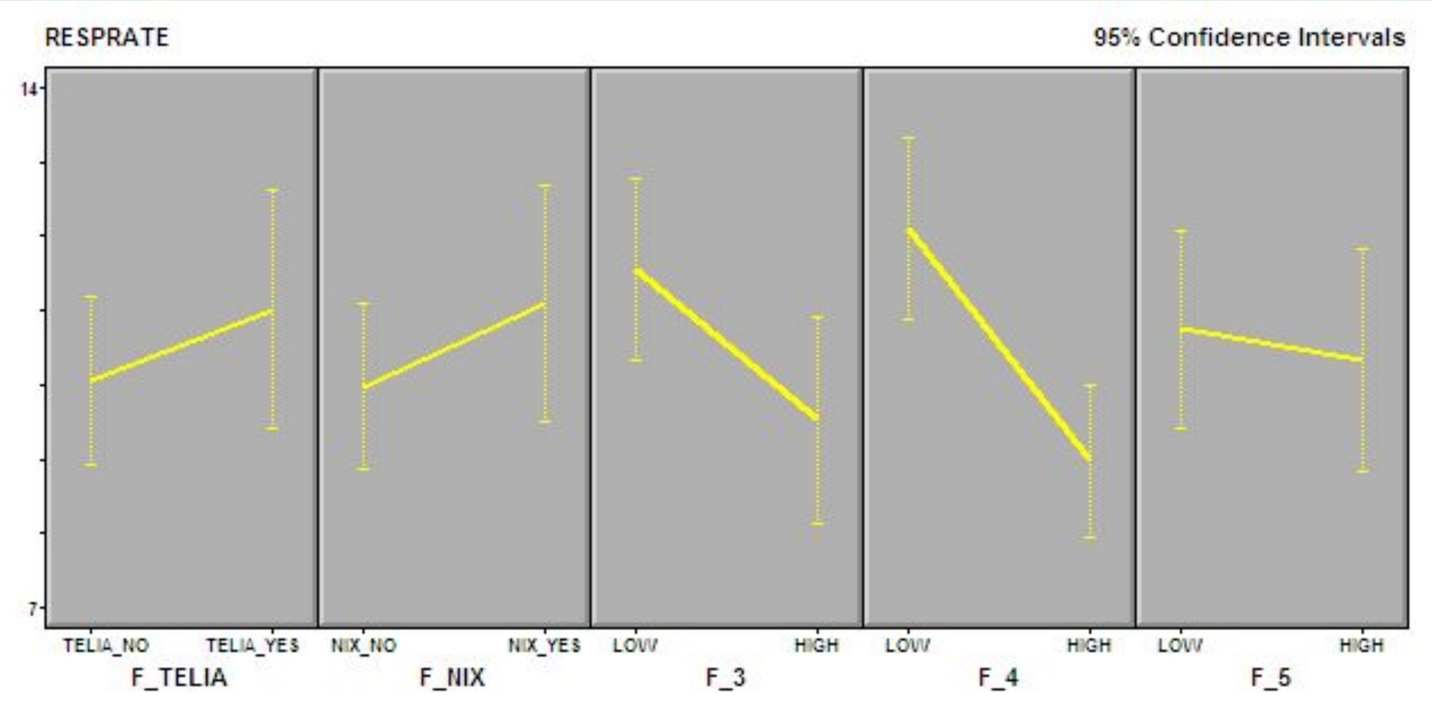
SAS QC / ADX Demo



Model Description

Effect	Estimate	Std Error	t Ratio	P Value
F_TELIA	0.95063	0.39631	2.3987	0.0534
F_NIX	1.1281	0.39631	2.8466	0.0293
F_3	-2.0269	0.39631	-5.1144	0.0022
F_4	-3.1206	0.39631	-7.8742	0.0002
F_5	-0.41563	0.39631	-1.0487	0.3347
F_TELIA*F_NIX	0.75437	0.39631	1.9035	0.1057
F_TELIA*F_3	-0.075625	0.39631	-0.19082	0.8550
F_TELIA*F_4	-0.46187	0.39631	-1.1654	0.2881
F_TELIA*F_5	-0.19188	0.39631	-0.48415	0.6454
F_NIX*F_3	0.99188	0.39631	2.5028	0.0464
F_NIX*F_4	-1.3369	0.39631	-3.3733	0.0150
F_NIX*F_5	0.025625	0.39631	0.064659	0.9505
F_3*F_4	-0.17937	0.39631	-0.45261	0.6667
F_3*F_5	0.68562	0.39631	1.73	0.1344
F_4*F_5	-1.3556	0.39631	-3.4206	0.0141
F_TELIA*F_NIX*F_3	0.79563	0.39631	2.0076	0.0915
F_TELIA*F_NIX*F_4	-0.64063	0.39631	-1.6165	0.1571
F_TELIA*F_NIX*F_5	-0.63313	0.39631	-1.5975	0.1613
F_TELIA*F_3*F_4	-0.098125	0.39631	-0.2476	0.8127
F_TELIA*F_3*F_5	0.72188	0.39631	1.8215	0.1184
F_TELIA*F_4*F_5	0.61313	0.39631	1.5471	0.1728
F_NIX*F_3*F_4	-0.42813	0.39631	-1.0803	0.3215
F_NIX*F_3*F_5	-0.10563	0.39631	-0.26652	0.7988
F_NIX*F_4*F_5	-0.021875	0.39631	-0.055197	0.9578
F_3*F_4*F_5	0.90563	0.39631	2.2851	0.0624

ADX: Fit Details for RESPRATE

Model Type: Predictive Model / Master Model

Overall ANOVA | Model Terms | Parameters

Source	DF	SS	MS	F	Pr > F
Model		59.2056	22.7437	10.4330	<.0001
Error		52.3194	2.1800		
(Lack of fit)		12.4863	1.5608	0.6269	0.7440
(Pure Error)		39.8331	2.4896		
Total		211.5250			

Response Mean	R-Square	Adjusted R-Square	Root MSE	C.V.
10.53844	0.752656	0.680514	1.476474	14.01037

Include block effect in predictive model

ADX: Fit Details for RESPRATE

Model Type: Predictive Model / Master Model

Overall ANOVA | Model Terms | Parameters

Model term	Coded data	Uncoded data
Intercept	10.5384375	13.3787500
F NIX	0.5640625	-1.4731250
F 3	-1.0134375	-1.0350000
F 4	-1.5603125	-3.1018750
F 5	-0.2078125	0.9400000
F NIX*F 3	0.4959375	-1.9837500
F NIX*F 4	-0.6684375	2.6737500
F 4*F 5	-0.6778125	-2.7112500

Include block effect in predictive model

- Model details – important factors
- Response equation

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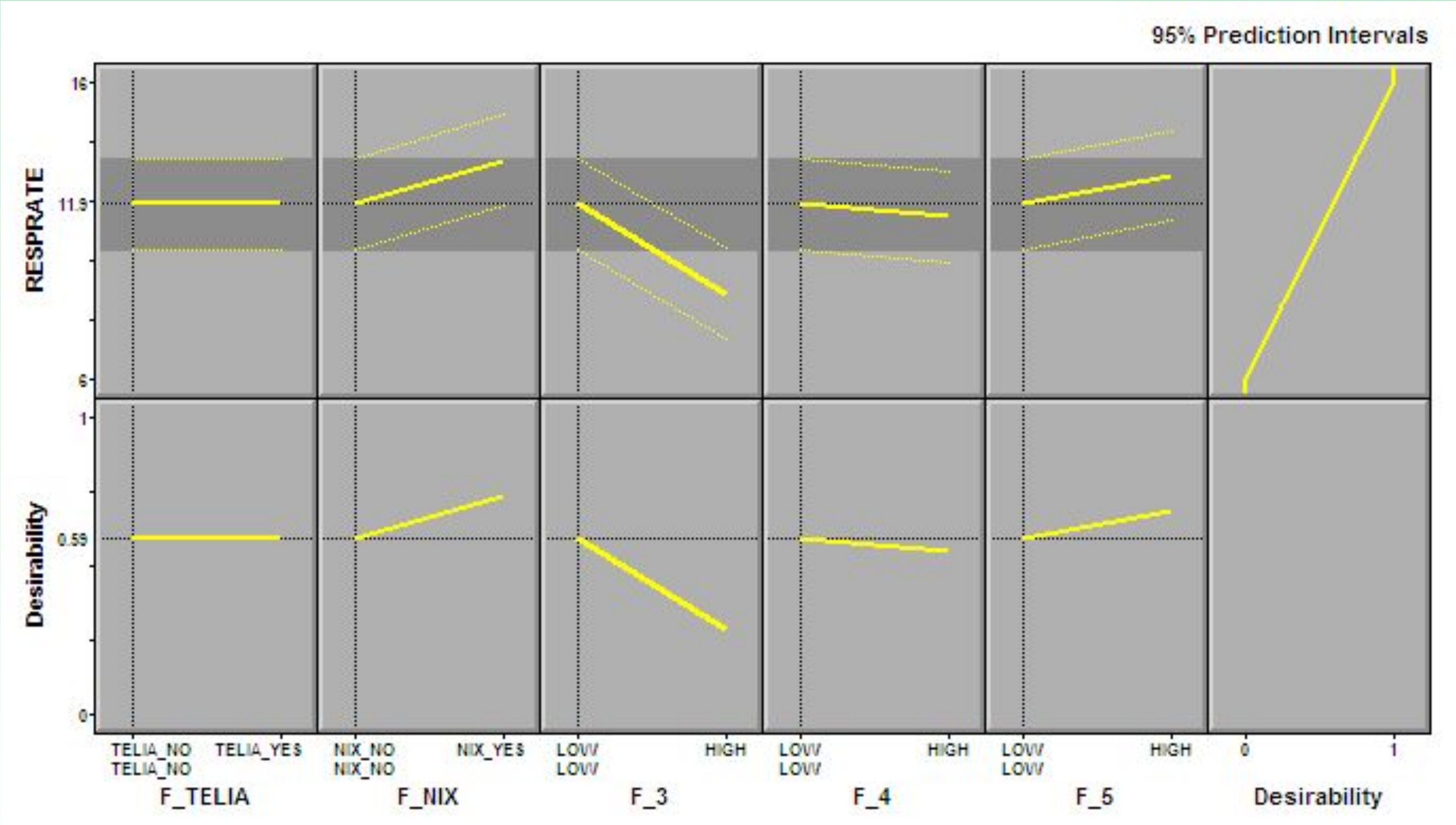
Response Optimization



- Use results from model to optimize fit, we can include a desirability function

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Case 1 Conclusion

- SAS QC / ADX is nice and easy to use
- Results are easy to explain
- Response rate is improved compared to random selection
- Method is conflicting with traditional predictive modeling

Case 2: Broadband – 3play

Workflow

- Define business problem
- Design test
- Run test campaign
- Build model
- Optimize scores
- Run campaign based on optimized scores

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Define Business Problem

- Increase sales in broadband subscriptions

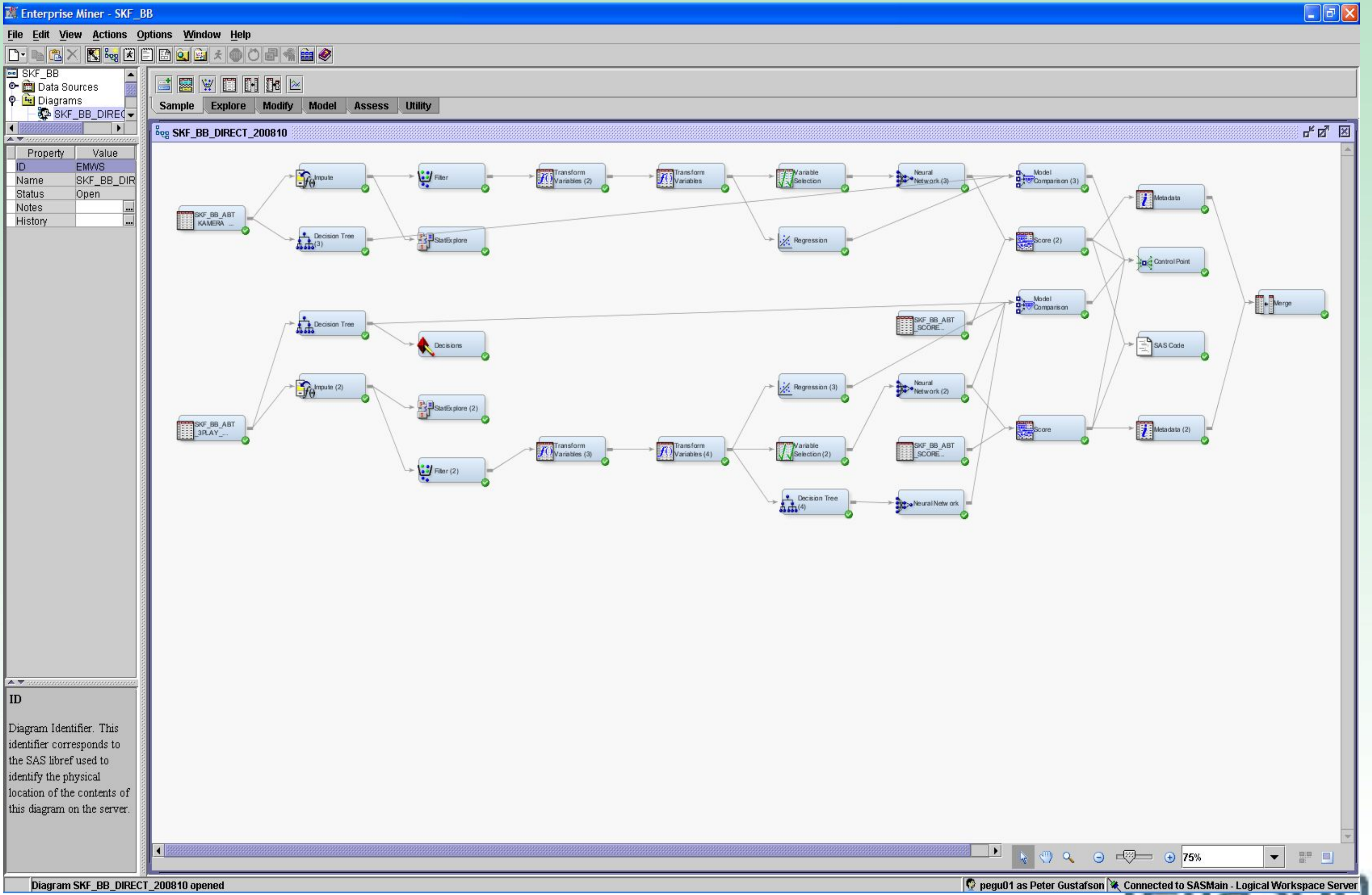
Design Test

- In this case we chose only one factor with two levels
- The factor is offer and the levels were two different offers
  - broadband standalone with a digital camera as a giveaway
  - 3play - a bundle with fixed line phone, broadband and IPTV
- Both offers had been tested before using broad media and performed good enough
- 2000 customers for each run were selected as sample size using proc power
- Purpose of this test is to find differences between customers accepting 3play versus the standalone offer

Run Test Campaign

- One telemarketing agency was used
- 60 customers accepted the camera offer and 75 customers accepted 3play
- Sales speech had to be revised during the campaign
- Acceptors who withdrew from the deal before delivery were considered as non-acceptors

Build One Model For Each Offer



Optimize Scores

CustomerID	P(3play)	P(Camera)	P(Max)	Winner
1	0.6	0.7	0.7	Camera
2	0.1	0.8	0.8	Camera
3	0.5	0.4	0.5	3play
4	0.4	0.3	0.4	3play

Case 2 Conclusion

Method	Estimated hit rate when contacting 20 000 customers
Random selection using best offer	7,5%
Predictive modeling using one offer	12 %
Predictive modeling using two offers	14 %

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Experiences and Learnings

You might succeed by experimenting with following

- Sell the concept to the decision makers
- Take a training course in DOE, use tools like Excel & QC to make design
- Be selective with analytical cases, start simple & easy
- Think what is truly wanted to be tested and measured
- Plan carefully, build a process, make sure it is followed
- Avoid Ad Hoc – continuity is key
- Consider combining DOE with traditional predictive modeling
- Attend operational meetings – discuss!
- Act on results!

Business Benefits, Goals Met, Plans

- We have better control over different campaign components
- We can select more intelligent target groups and measure results more efficiently

- We continue by
  - Researching and experimenting with more advanced designs
  - Including experimentation as part of every campaign
  - Improving process even further

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Summary

- We have improved direct marketing results and process
- We have better control over direct marketing activities, we know how to find out important factors and their effects
- In order to benefit from learnings, work must be executed in a structured and cohesive way

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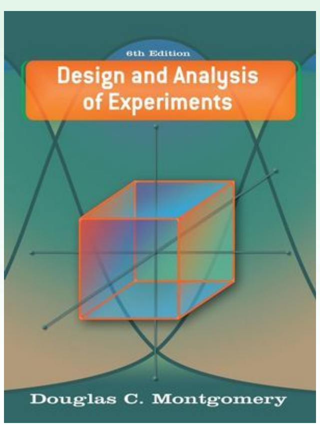
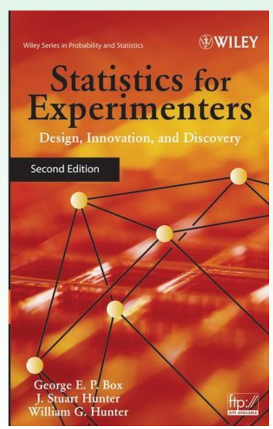
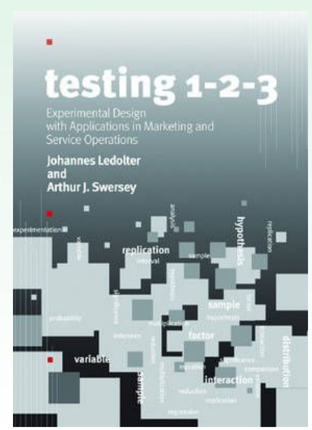
Recommended Books etc.

- Design and Analysis of Experiments , Douglas Montgomery, Wiley 2004, ISBN 047148735X
- Statistics for Experimenters: Design, Innovation, and Discovery , 2nd Edition, Box, Hunter, Hunter, Wiley-Interscience 2005, ISBN 0471718130
- Testing 1-2-3: Experimental Design with Applications in Marketing and Service Operations, J. Ledolter & A. Swersey, Stanford Business Books 2007, ISBN 0804756120
- SAS training course: Design of Experiments for Direct Marketing
- http://www.google.com & http://en.wikipedia.org/wiki/Category:Experimental_design







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Thank You! – Questions?

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