CSX415Data Science Principals and Practice

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Christopher Brown

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Courses Taught

- Practical Machine Learning
- Data Science Principles and Practice

Christopher Brown has spent the last 18 years as a consultant in a variety of industries: Financial Services, Health Care, Retail, Defense, etc. **Chris** also teaches statistics and computer science at the University of California, Berkeley.

Chris and his teams are frequent contributors to Open Source Software in a variety of projects and programming languages.







We help our client

use data to make (better) strategic and operational decisions.

- Strategy
- Organizational Structure
- Talent
- Execution
 - Data acquisition
 - Data organization (ETL & data warehousing)
 - Data consumption (data science/analysis/ML)
 - Analytical application development

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Goals

best kept secrets of

• • •

Data science and machine learning

Organization

Roles and responsibility

Project lifecycle

Tech stack

DataMining DataMining Statistics Phing DataScience ArtificialIntelligence AdvancedAnalytics SupervisedLearning
DeepLearning
ReinforcementLearning
UnsupervisedLearning
MachineIntelligence

Data Science



Oh Really ...

Data Scientist:

The Sexiest Job of the 21st Century

Meet the people who can coax treasure out of messy, unstructured data. by Thomas H. Davenport and D.J. Patil

hen Jonathan Goldman arrived for work in June 2006
at LinkedIn, the business
networking site, the place still
felt like a start-up. The company had just under 8 million
accounts, and the number was
growing quickly as existing members invited their friends and colleagues to join. But users weren't

seeking out connections with the people who were already on the site at the rate executives had expected. Something was apparently missing in the social experience. As one LinkedIn manager put it, "It was like arriving at a conference reception and realizing you don't know anyone. So you just stand in the corner sipping your drink—and you probably leave early."

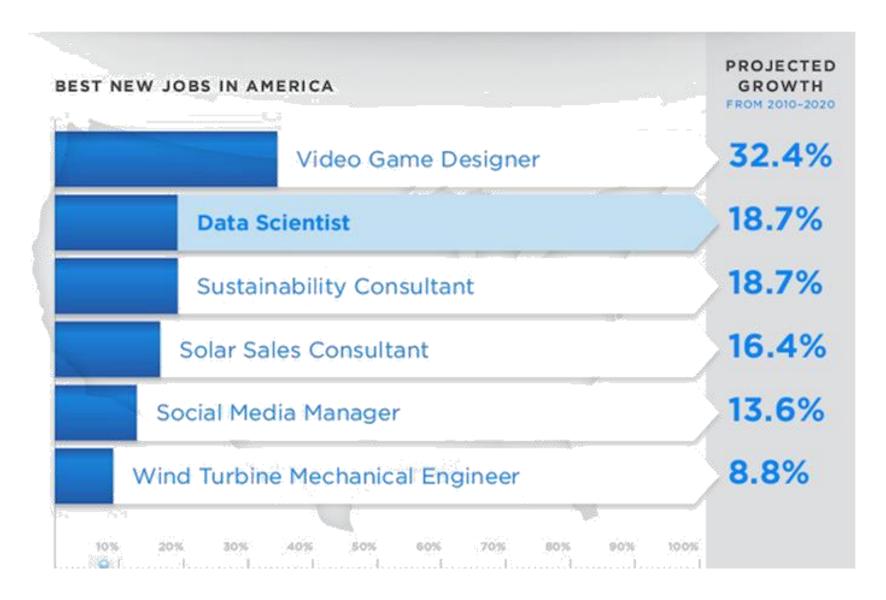
THE WORLD NEEDS DATA SCIENTISTS



IF YOU ARE A MATH- OR DATA-DRIVEN INDIVIDUAL LOOKING FOR THE PERFECT CAREER FIT, look no further than data science. Due to the ongoing explosion of big data, companies have more information at their fingertips than ever—and not enough people who can make sense of it all. This reality has created a big market for quantitative analysts and individuals who can put massive amounts of data into perspective. Take a look.

Source: http://venturebeat.com/2013/11/11/data-scientists-needed/

CAREERS IN DEMAND





15,000%

ACCORDING TO FICO, THERE WAS A 15,000% INCREASE IN JOB POSTINGS FOR DATA SCIENTISTS

Currently the job market seeks

140,000-190,000

OPEN POSITIONS.

IN ADDITION,

1.5 million

data literate managers will need to be retrained or hired to meet needs.

Salary

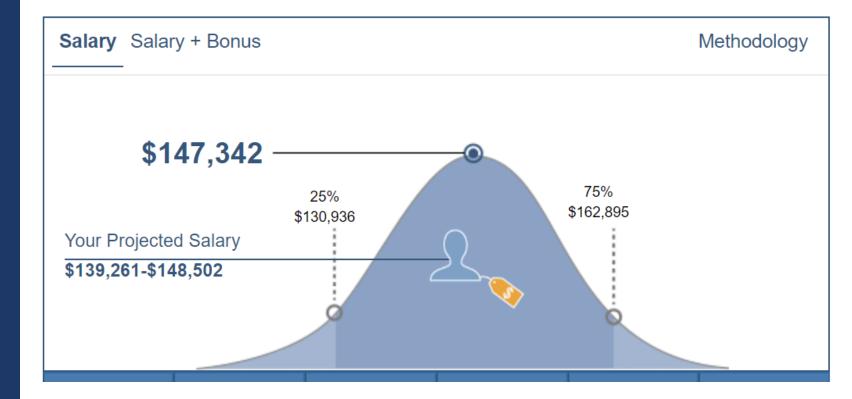
Mid-level Data Scientist

Des Moines, IA\$114,784Redmond, WA\$129,875San Francisco, CA\$147,342

Data Scientist IV Des Moines, IA

Data Scientist IV Redmond, WA

Data Scientist IV San Francisco, CA



Source: Salary.com

Additional Expenses

- Bonus +
- Overhead +
- Technical Resources +

\$150,000+ per data scientist

Data science is expensive

... great impact on the viability of projects

... how can we make it cheaper or more efficient?

Same as anything ...

develop *efficient* and *repeatable* processes automating those parts that make sense.

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What is Data Science?



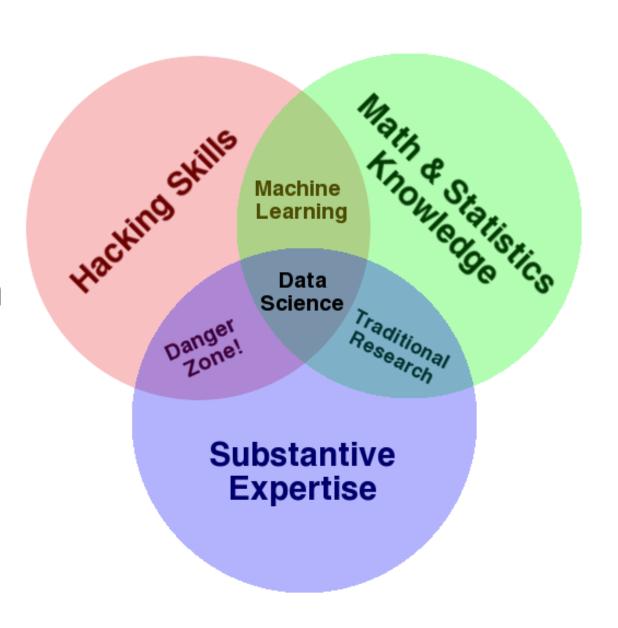
An interdisciplinary **field** about scientific methods, processes and systems to extract knowledge or insights from data in various forms, either structured or unstructured, [1][2] similar to Knowledge Discovery in Databases (KDD).

There is no consensus ...

definition of data science.

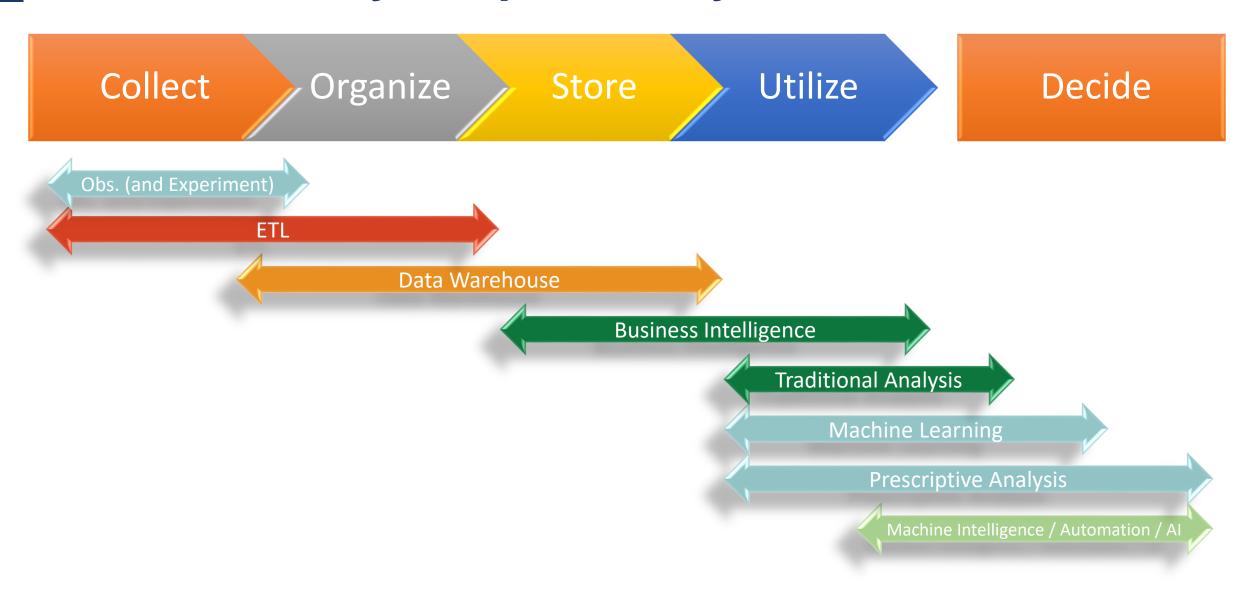
Data Science by Skill Set

Data Science Venn Diagram



Ref. http://drewconway.com/zia/2013/3/26/the-data-science-venn-diagram

Data Science by Responsibility

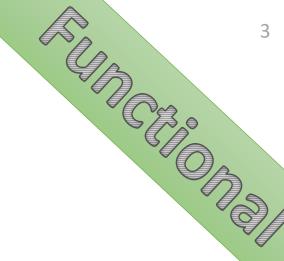


Data Science ≠ Machine Learning

Data Science by Function

The process/practice of using data

Collect >> Organize >> Store >> Utilize



In order to

- Understand or explain (traditional statistical analysis)
- aid or automate <u>decision making</u>

Data Scientists only do 7 things



Determining the state of your business, application or process

- at a future time?
- and/or in a diff. environment?

Examples

Macro

- Profit/ROI Forecasts
 - Revenues
 - Cost
- Capacity and Resource Planning (ERP)

Micro

- Product Demand (PD)
- Member Lifetime Value (MLV)



Forecasting



Rare Event Detection

Identify outliers or observations with interesting or aberrant characteristics?

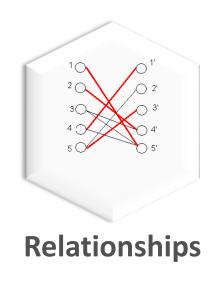
(before those characteristics are known/observed)



Rare Event Detection

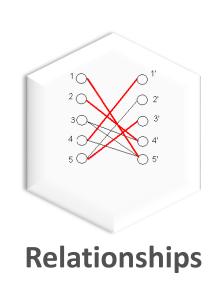
Examples

- Member Attrition
- Risk events (Fraud/Default)
- Security (anomaly detection, network intrusion)



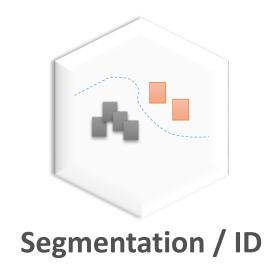
Determine

- the type and/or strength of relationship between two things?
- Do you have anything to recommend?



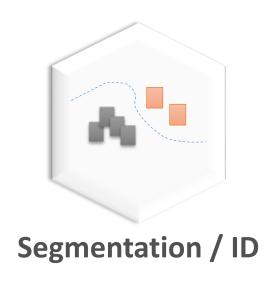
Examples

- Recommendation (product member)
 - Product recommendations
- Affinity or similarity (member member)
 - CU Evangelists
- Co-occurrence / Market Basket Analysis (product – product)

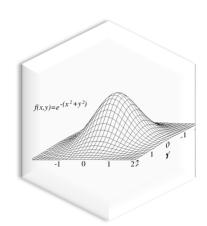


Determine how people or things are group together for :

- promoting understanding of a system?
- Implementation of a (often complex) strategy?



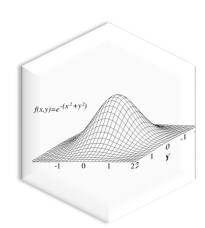
- What are my member segments (usually related to a need or outcome)
- •What do I market to existing or potential members?
- How are member support reps alike or different?



Optimization

Determine the best choice

- among a (possibly infinite) number of possibilities and/or
- with a one or more constraints?



Optimization

Resource allocation

- Which sales and marketing opportunities should be pursued?
 How do I deploy a fixed sales staff?
- •How do I apportion budget(s)?
- How do I most effectively partition my (limited) set of efforts?



Identify the *causes* that bring about various *outcomes*?

Causal Analysis



- Key Driver Discovery
- •What are profits key drivers?
- •What are product features driving adoption? (stickiness)



Data Collection

Do you need more data and want to

- ensure that the right information is collected
- efficiently as possible?

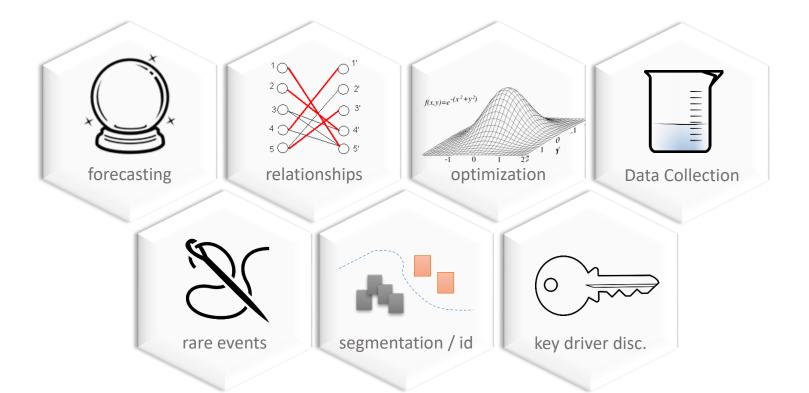


Surveys: how to collect data concerning a topic of interest.

What future application features are most desirable?

Design of experiments: how to expend the least effort to get the data in order to answer the best question.

Levers – what levers need to be pulled to enhance/maximize member acquisition?



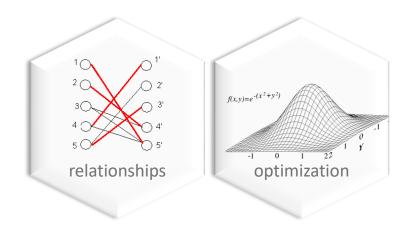
No so fast

Solutions are not that simple

Solutions often involve more than one techniques

Recommend a product ...

that increases stickiness!



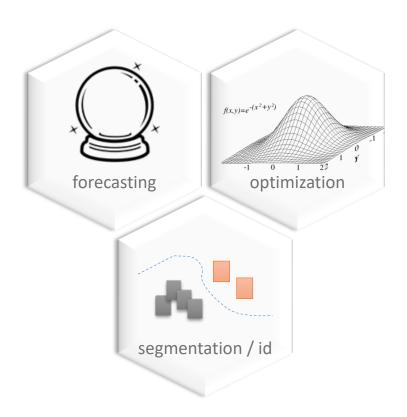
Provide member-tailored experiences that ...

lead to *deeper adoption*



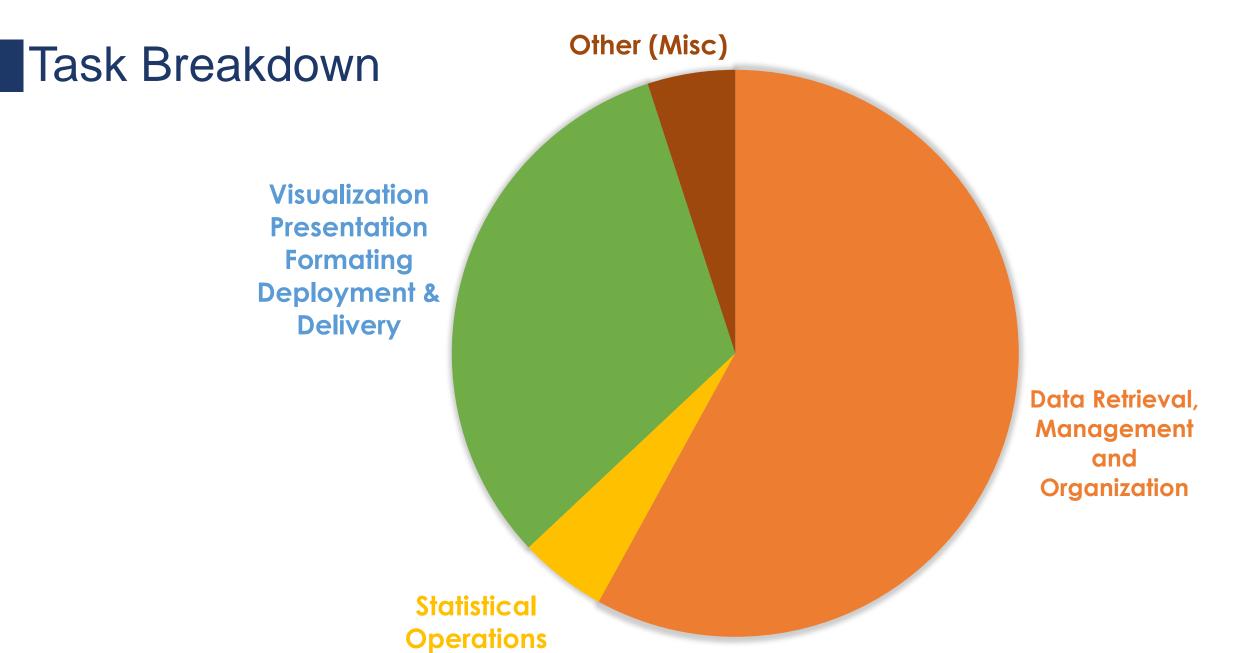
Which opportunities/leads should be pursued first...

to increase revenues



Improve member support outcomes by setting *optimal staffing levels, skills coverage and schedules*





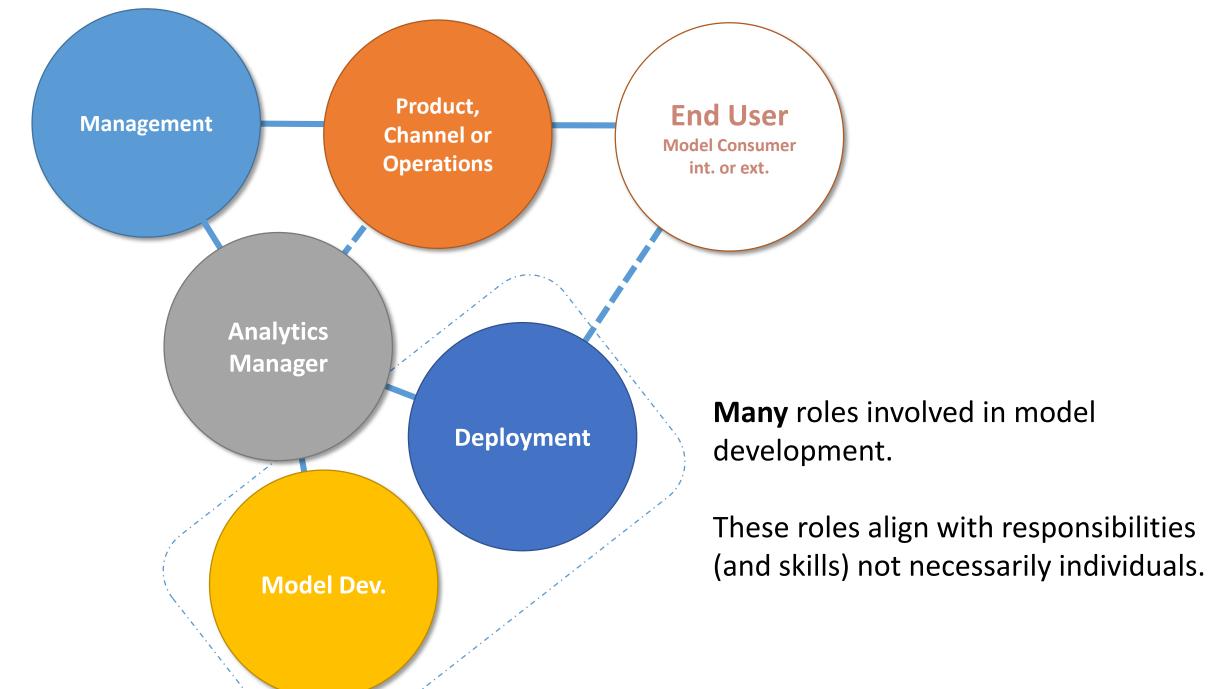
Data Science in the Organization

as Technical Discipline

as Business Discipline

Reports to technical organization usually closely associated with DW or BI team.

Reports to channel, product or operational department





 Ensure proposed project aligns with organization strategic objectives

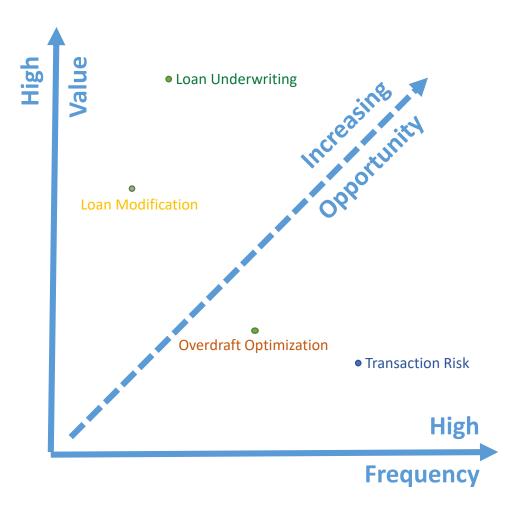
- Ensure benefits outweigh cost
 - Positive ROI

Ensure project is prioritized

Track ongoing performance

Types of Decisions

- High Frequency
- High Value*



^{*} relative to existing operations or systems

Management Success is ...

having a model addressing the right opportunity with the expected impact



Estimate benefits

Identify deployment endpoints

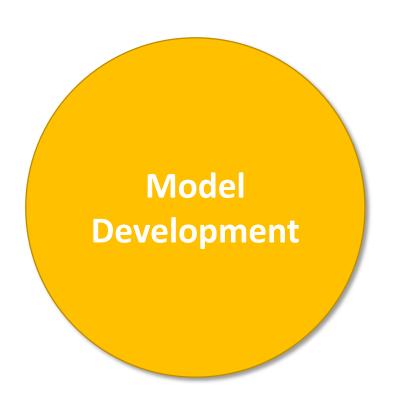
User testing

Change management

Identify business risk



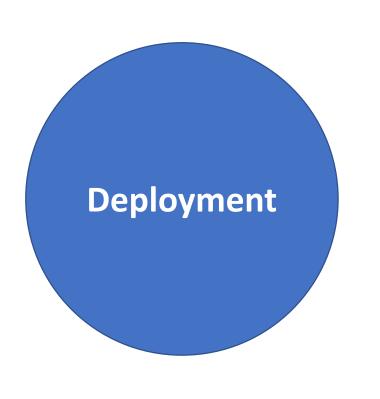
- Consult with internal client (Product, Client or Operations)
 - Gather Requirements
- Manage Model Development and Deployment
- Enforce standards
- Testing
- Track performance metrics



- Build Model
 - Model specification
 - Feature Specification
 - Calibration

Document model

Ongoing model evaluation and maintenance model



 Use feature specification and model specification to operationalize model

 Deliver scores to deployment endpoints

Test and maintenance deployment

Inception

5 Phases

Model Management

Formalization

Deployment

Model Development



"I want help deciding ..."



Determine Goal(s)

- State benefits
- Success criteria (near/long term)
- Timeline

Identify Data Sources (especially responses)

- Deployment (if applicable)
 - Use / delivery of model(s)



2 Formalization

Formalize goals

Identify success metric

Quantify success criteria

Review Data Resources

Identified SME

Plan

Estimate effort/time line Identify resources needed

"You said ...
which means"





3

Model Development

Develop Code for

- Retrieving and cleansing data
- Transforming raw data into features
- Training model
- Scoring observations

Output

- Model Code/Specification
- Report on Model Performance

"this is what ... can be done..."





4

Model Deployment

"getting you what you want...where and when you want it"

Determine how and how often models are consumed:

- One time report
- Repeated reporting (BI)
- Applications
 - Embedded
 - Stand-alone Decision App
- Version controlled code for deployment



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Model Management

"ensuring you get what you want..."

Monitoring

Model review and re-training (if necessary)

- Based on schedule
- Based on performance

Continued development / Model improvements

Output: Performance Report