

DATA SCIENCE with SMALL TEAMS

Drew Fustin

PhD, Physics

Lead Data Scientist



**SPOT
HERO**

drewfustin@gmail.com | 7.5.2016 | PyData Chicago

DATA SCIENCE

with

SMALL TEAMS



Or:

Lots of Advice I Need to
Hear and Apply Myself

DATA SCIENCE with **SMALL TEAMS**

Forward:

This is not an indictment of companies with limited resources. It's a description of a challenging reality. A reality I happen to love and find incredibly exciting.

DATA SCIENCE

according to Jeremy Stanley, VP of Data Science at Instacart

DECISION SCIENCE

use data to analyze business metrics – such as growth, engagement, profitability drivers, and user feedback – to inform strategy and key business decisions.

DATA PRODUCTS

use data and engineering to improve product performance, typically in the form of better search results, recommendations, and automated decisions.

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DECISION SCIENCE

Wait, isn't that BI?

The differences are blurry, but decision science shouldn't be producing reports and dashboards. It's often the things that go *in* to BI solutions beyond aggregates and KPIs. It should be things beyond what BI tools can deliver, like forecasting and clustering and other statistical and coding-based techniques.

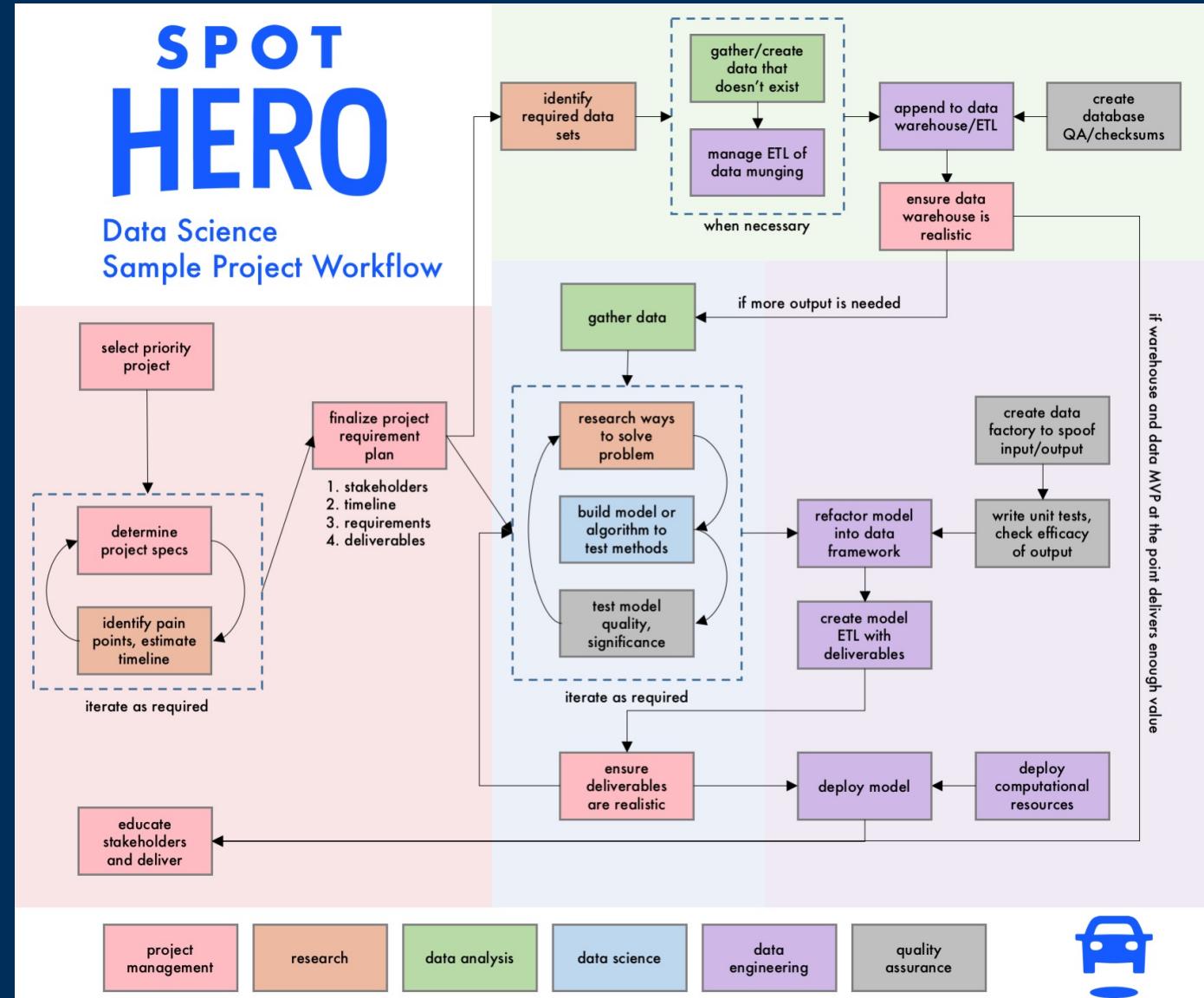
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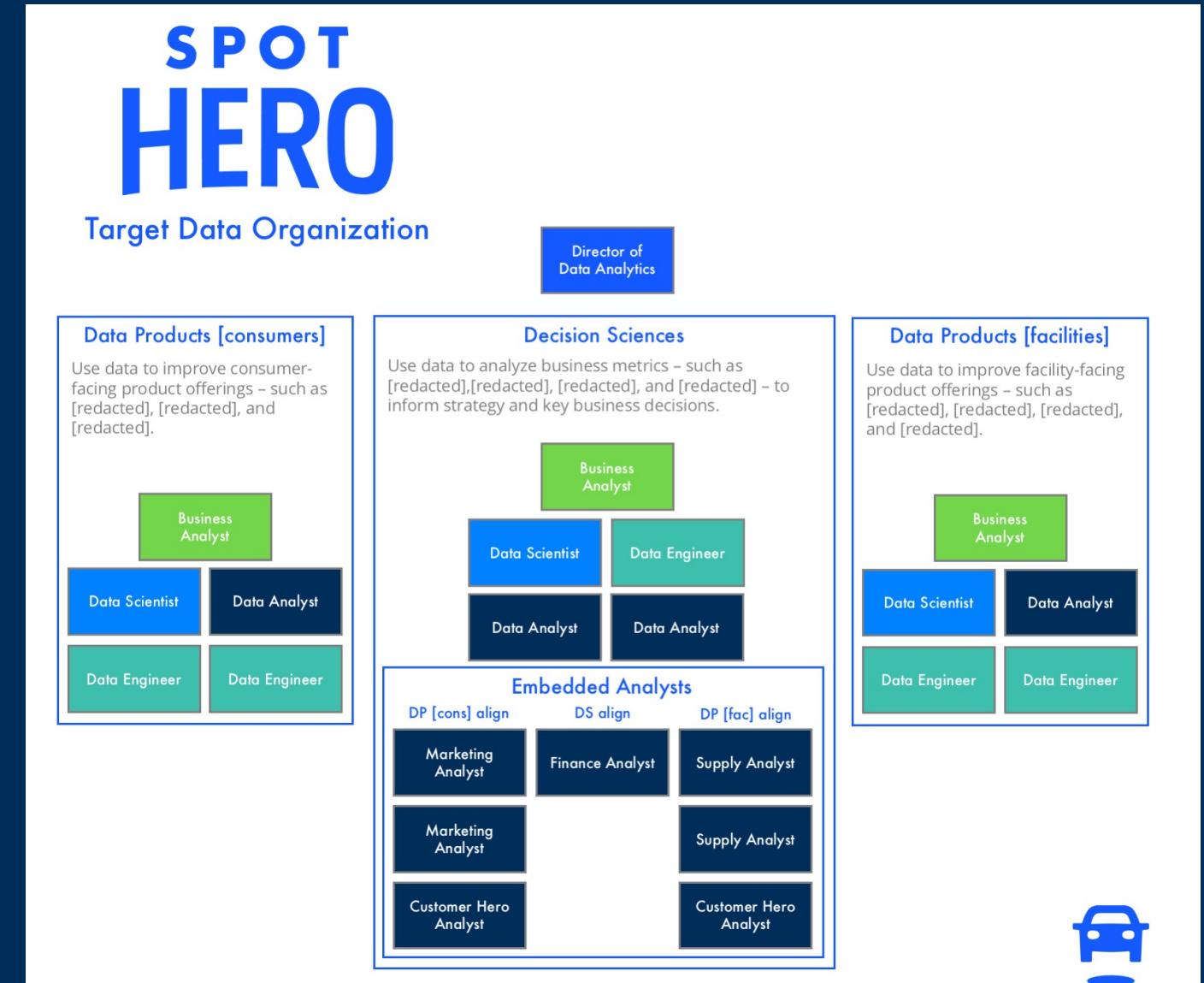
“While decision science and data products call for some of the same skills, it’s rare for data scientists to excel at both. Decision science depends on business and product sense, systems thinking, and strong communication skills. Data products require machine learning knowledge and production-level engineering skills. If you have a small data science team, you may need to find the rare superstars who can do both. But you’ll benefit from specialization as you scale your team.”

[Doing Data Science Right – Your Most Common Questions Answered \[Jeremy Stanley and Daniel Tunkelang\]](http://firstround.com/review/doing-data-science-right-your-most-common-questions-answered/)
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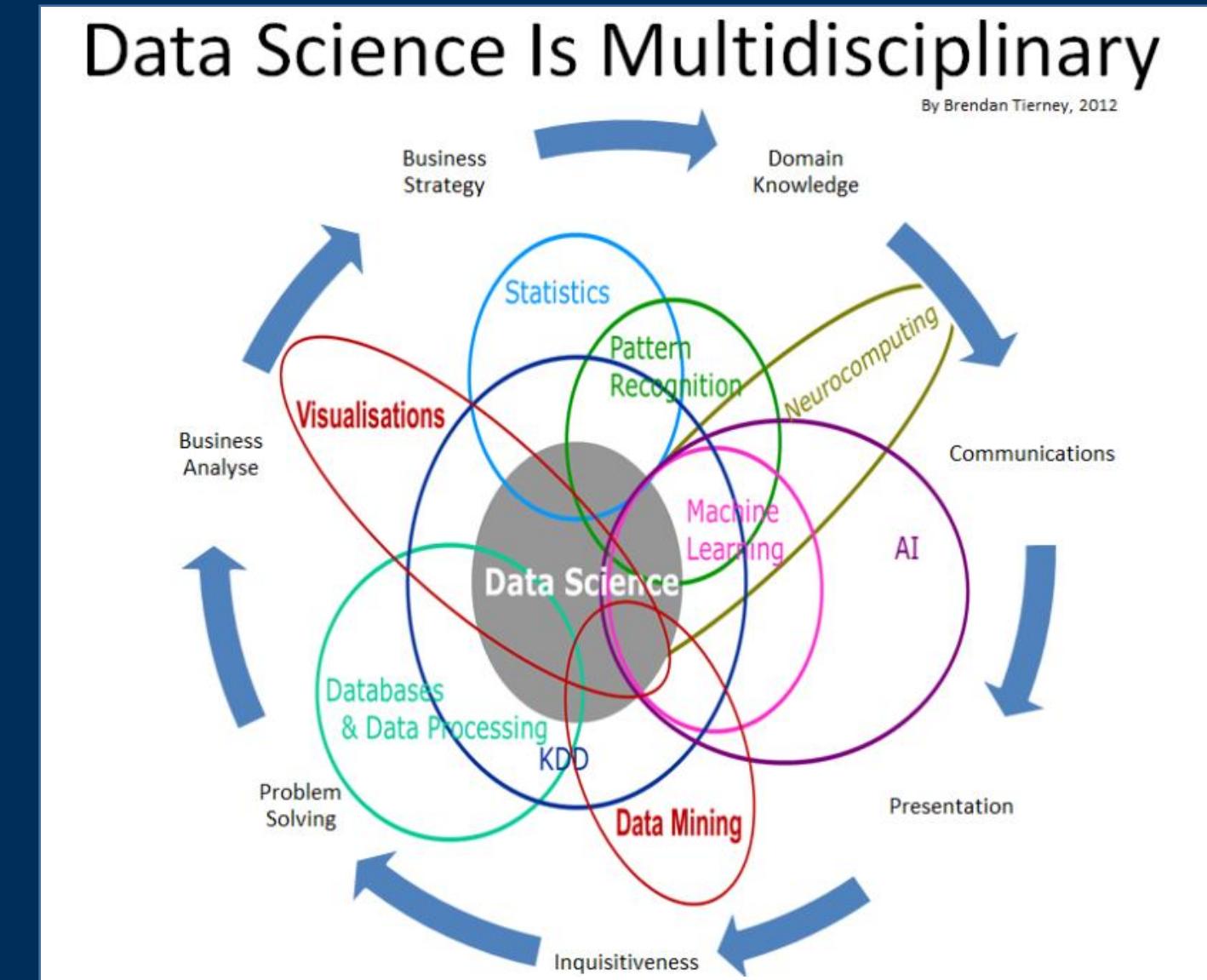
DATA SCIENCE IS COMPLICATED



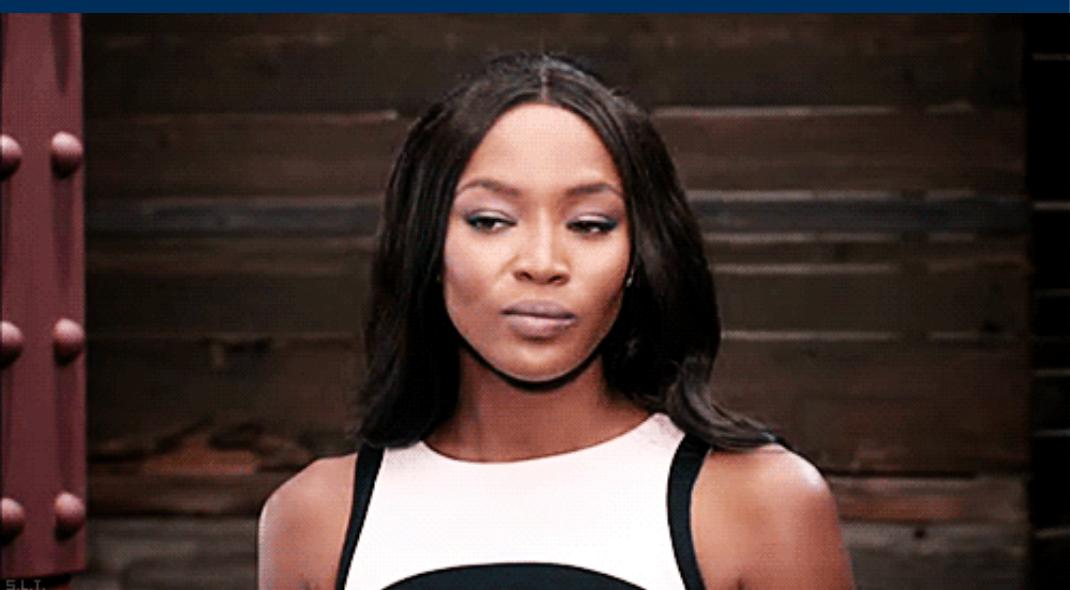
DATA SCIENCE IS EASIEST WITH A TEAM



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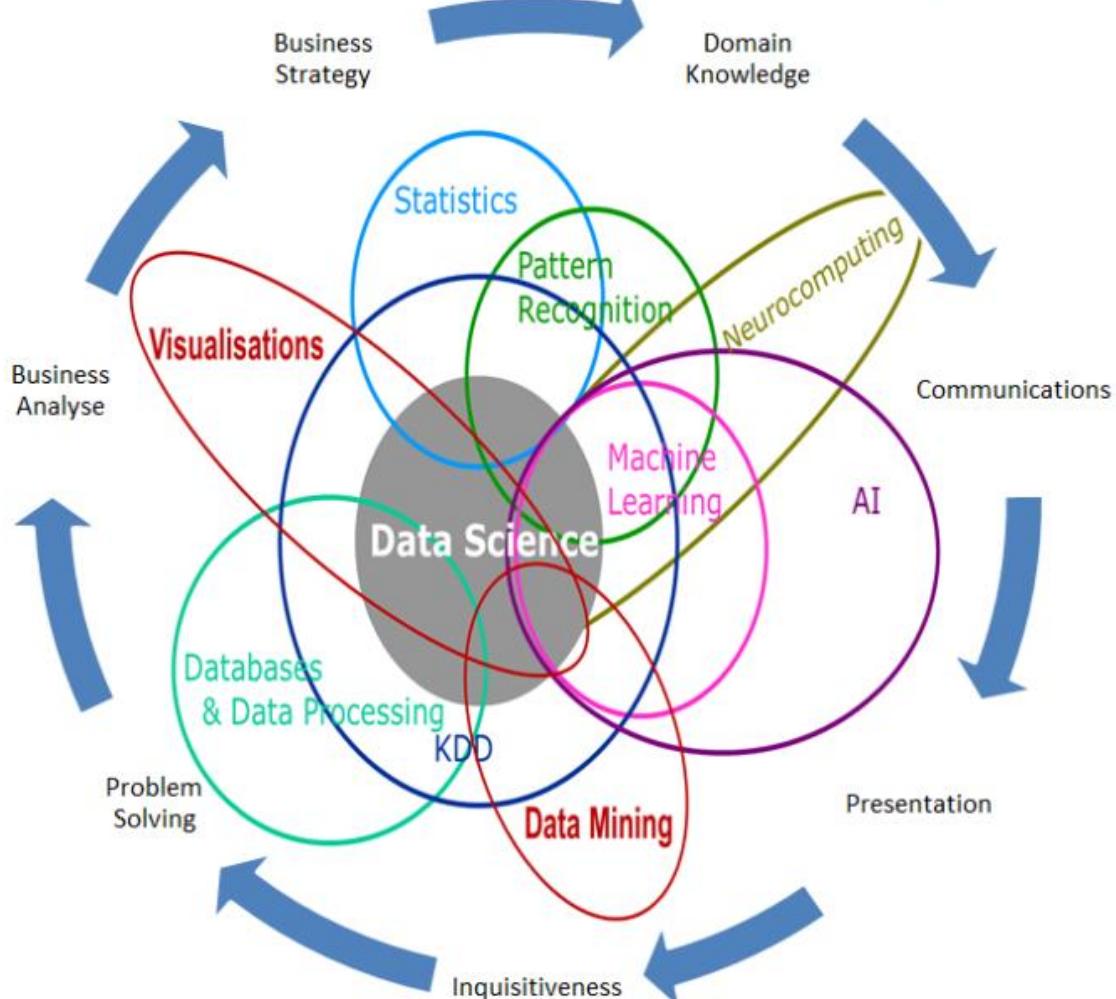


DATA SCIENCE

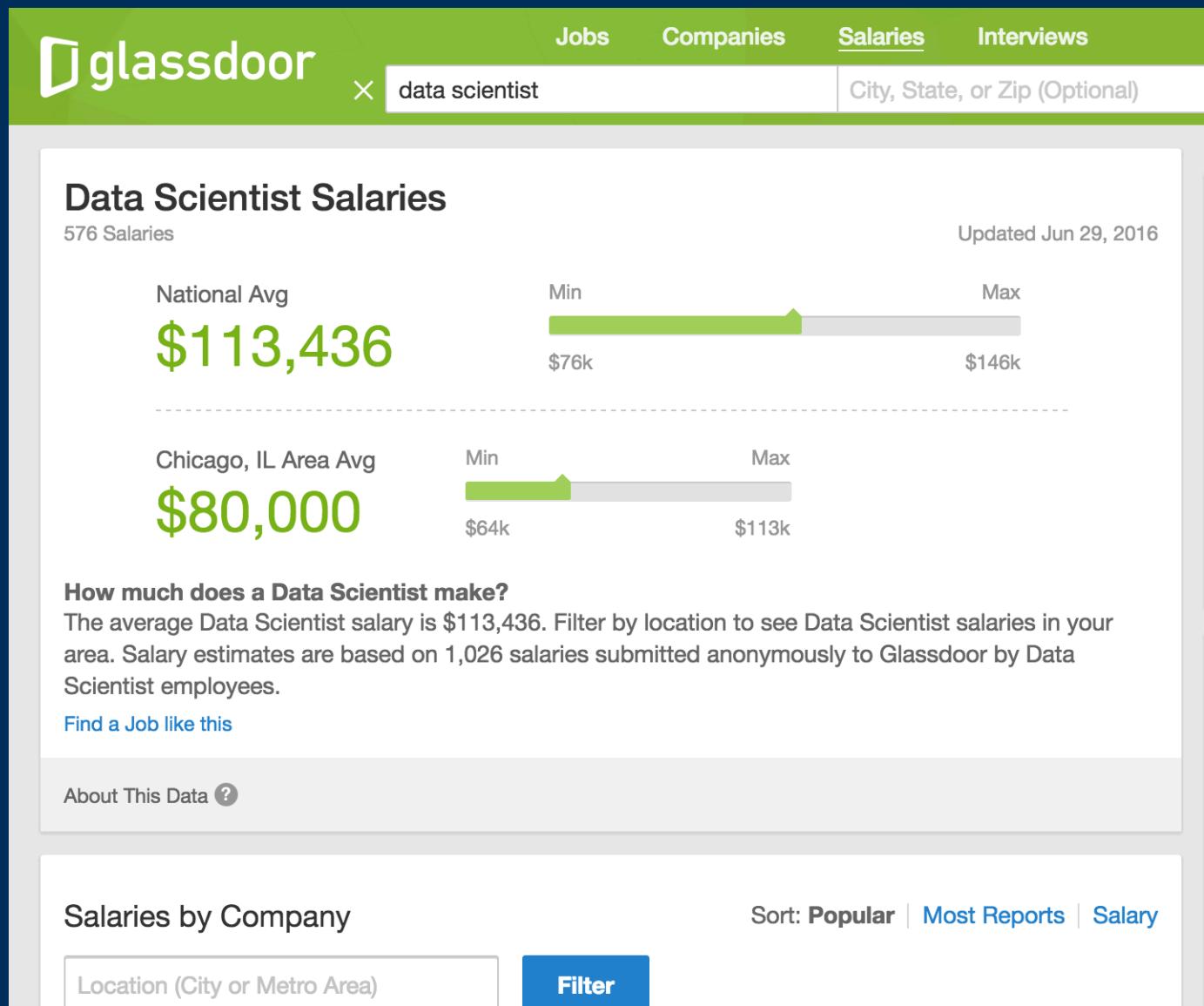


Data Science Is Multidisciplinary

By Brendan Tierney, 2012



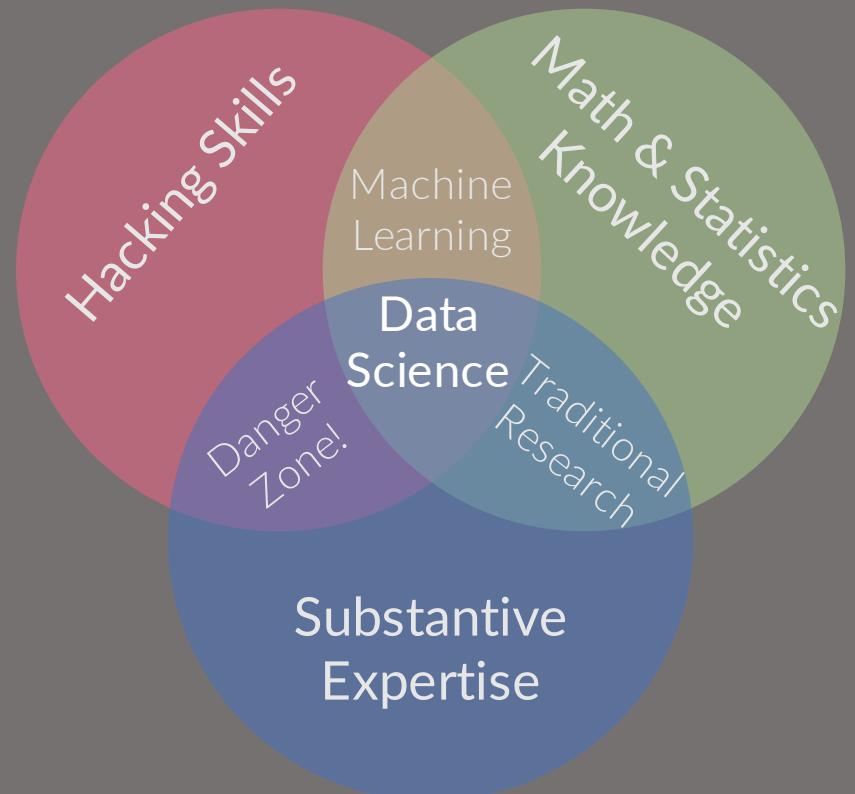
DATA SCIENCE IS EXPENSIVE



DATA SCIENCE

according to Drew Conway, CEO of Alluvium

NOT ALL
VENN DIAGRAMS
ARE USELESS

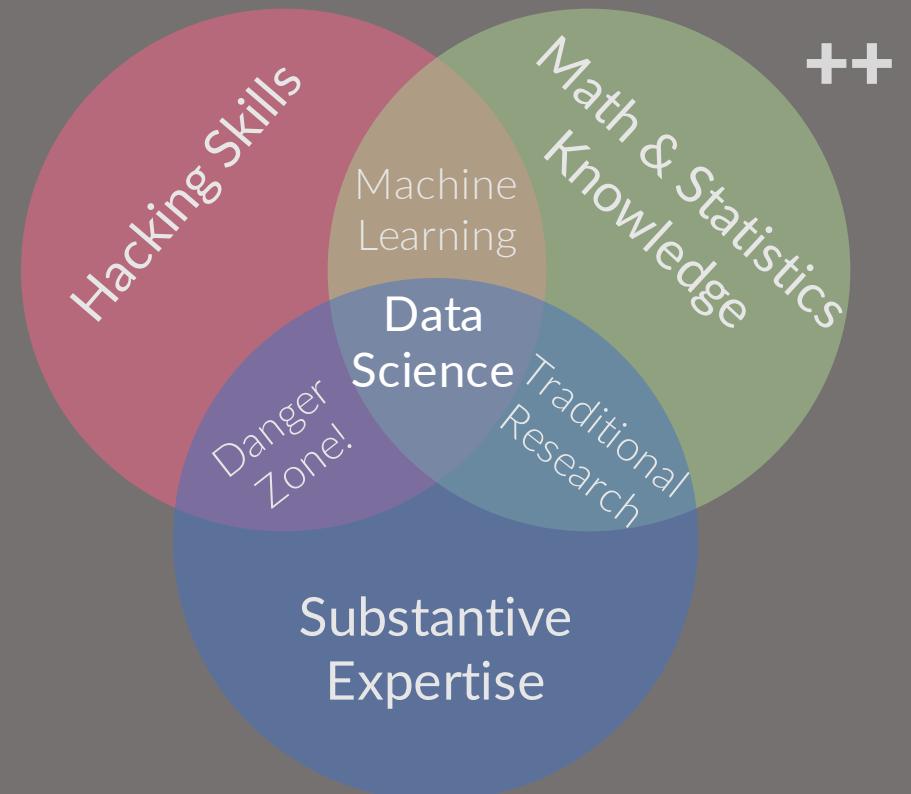


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**SMALL TEAM?
YOU CAN'T JUST BE A
DATA SCIENTIST**

You must be your own Product Manager
and User Experience Researcher



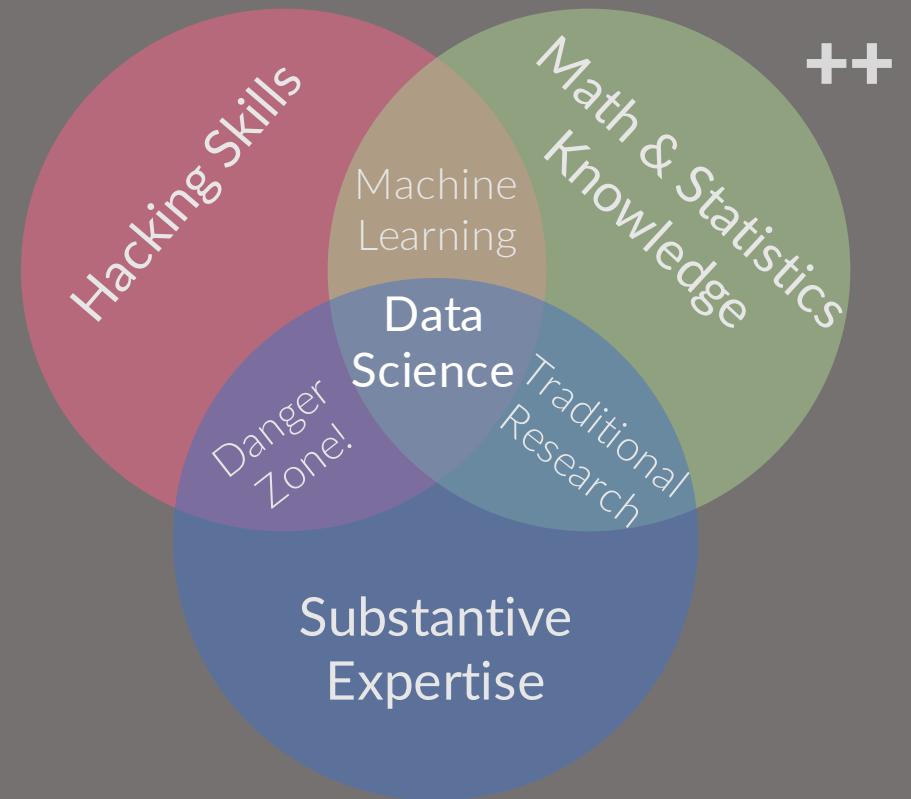
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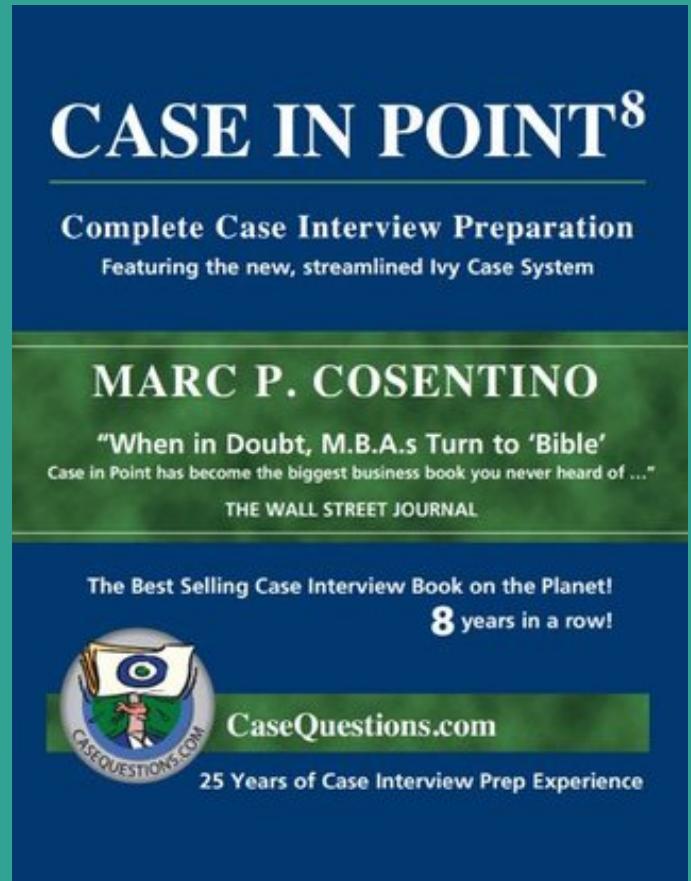
Sorry, but... 20% goes to COMMUNICATION



PM + UX

FROM ACADEMIA?

Learn to speak
strategy and business
GROSS MARGIN, KPIs, LTV, CAC,
ATTRIBUTION, ROI, RETENTION,
ATTRITION, MONTHS-TO-PAYBACK,
blah blah blah



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according to Arthur Geoffrion, UCLA Anderson School of Management

RESERVE THE RIGHT OF PROBLEM FORMULATION

Maxims for Modelers [Arthur Geoffrion]

<http://www.anderson.ucla.edu/faculty/art.geoffrion/home/docs/Gudmdl2.htm>

PM + UX

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DEVELOP A CLEAR CHARTER AND PROJECT PLAN

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FIND A HIGH-LEVEL CHAMPION

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ESTABLISH PERSONAL CREDIBILITY AND PRODUCE RESULTS EARLY

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INVOLVE THE STAKEHOLDER AND FUTURE USERS AT ALL STAGES

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COMMUNICATE OFTEN AND WELL

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OUR GOAL

FOCUS

or

EXPAND

when it works to stay small

provide a customer solution
and iteratively add features to
this solution to expand product

when scale is needed to be impactful

eventually grow a team of
complementary parts to allow for
increased scope

FOCUS

e.g. SaaS Data Product or Marketing Optimization Decision Science

CRITICAL: DON'T DO TOO MANY THINGS

Understand through UX and set expectations of stakeholders to deliver exactly what is needed.

Nothing more.

FOCUS

e.g. SaaS Data Product or Marketing Optimization Decision Science

UNIT TEST ALL THE THINGS

While unit tests are always important, when a product is built iteratively, they are necessary. Have data factories to spoof typical/edge case data.

FOCUS

e.g. SaaS Data Product or Marketing Optimization Decision Science

DOUBLE THE DOCUMENTATION

Explain the process technically (for future you)
and accurately but simply (for the consumer)

EXPAND

e.g. Recommendation Engines + Attribution Models + Routing Algorithms + ...

CRITICAL: QUICK TO “GOOD ENOUGH”

You need to scale the team to be effective, so produce small, easy wins to earn favor and budget. Think Pareto’s principle: 80% quality at 20% time cost.

EXPAND

e.g. Recommendation Engines + Attribution Models + Routing Algorithms + ...

GET DATA MVPs INTO PRODUCTION

Many Data Products require lots of user data,
so get an MVP out to start collecting,
and wait to improve.

EXPAND

e.g. Recommendation Engines + Attribution Models + Routing Algorithms + ...

BE A PRETTY GOOD DATA ENGINEER

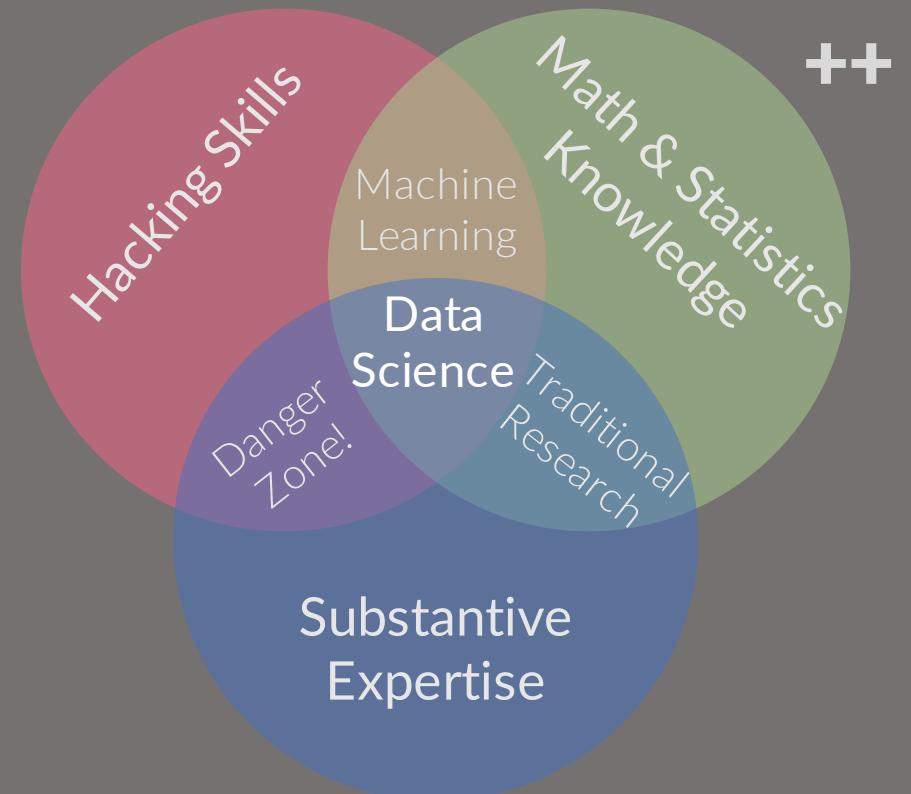
Projects are often standalone,
so have a reliable ETL process to reduce upkeep.
Upkeep time budget will increase over time.

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**SMALL TEAM?
YOU CAN'T JUST BE A
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You must be your own Product Manager
and User Experience Researcher

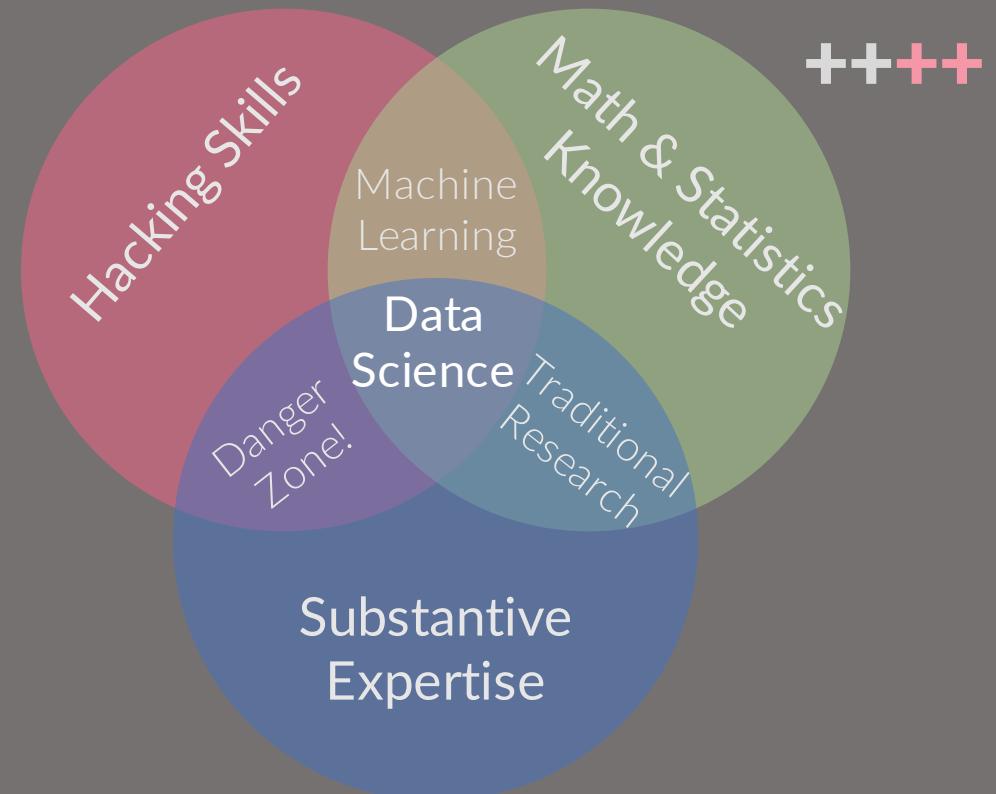


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**SMALL TEAM?
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You must be your own Product Manager
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and Data Engineer and QA Test Engineer

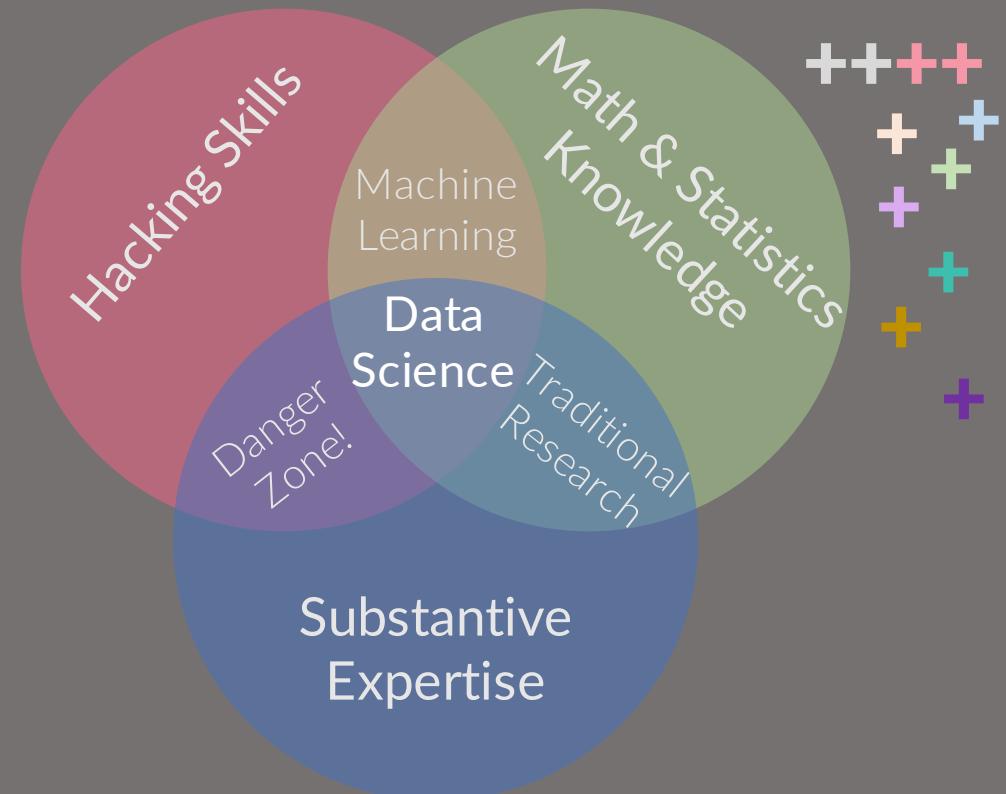


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AN ASIDE

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Lest you feel overwhelmed:
You don't have to be *great* at all of this.

AN ASIDE

Lest you feel overwhelmed:
You don't have to be *great* at all of this.

The beauty of being part of a small team is that what you contribute is probably going to be significantly better than what already exists.

ALSO...

DON'T BE A PHYSICIST.

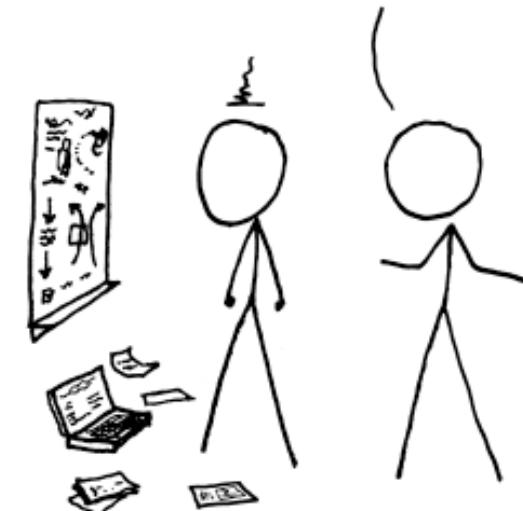
PEOPLE WHO ACTUALLY DO
THESE JOBS?

THEY'RE BETTER THAN YOU AT
DOING THEM.

YOU'RE TRYING TO PREDICT THE BEHAVIOR
OF <COMPLICATED SYSTEM>? JUST MODEL
IT AS A <SIMPLE OBJECT>, AND THEN ADD
SOME SECONDARY TERMS TO ACCOUNT FOR
<COMPLICATIONS I JUST THOUGHT OF>.

EASY, RIGHT?

SO, WHY DOES <YOUR FIELD> NEED
A WHOLE JOURNAL, ANYWAY?



LIBERAL-ARTS MAJORS MAY BE ANNOYING SOMETIMES,
BUT THERE'S NOTHING MORE OBNOXIOUS THAN
A PHYSICIST FIRST ENCOUNTERING A NEW SUBJECT.

<https://xkcd.com/793/>

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EXAMPLE

MY EVERYDAY TOOLKIT

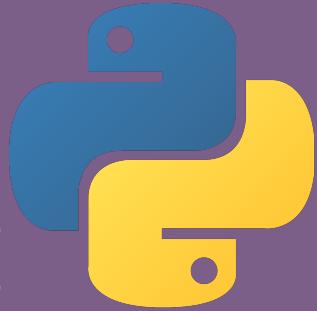
EXAMPLE

MY EVERYDAY TOOLKIT

PYTHON 3 + ANACONDA



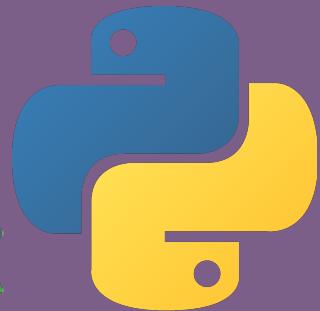
ANACONDA®



EXAMPLE

MY EVERYDAY TOOLKIT

**PYTHON 3 + ANACONDA
+ JUPYTER + PLOTLY**



EXAMPLE

MY EVERYDAY TOOLKIT

PYTHON 3 + ANACONDA
+ JUPYTER + PLOTLY
+ PANDAS

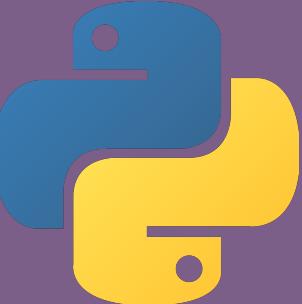
pandas
 $y_{it} = \beta' x_{it} + \mu_i + \epsilon_{it}$



plotly



ANACONDA®

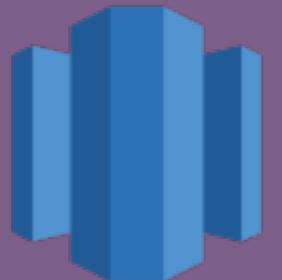


EXAMPLE

MARKETING OPTIMIZATION AT SPOTHERO

DATA COLLECTION

Transaction data in AWS Redshift



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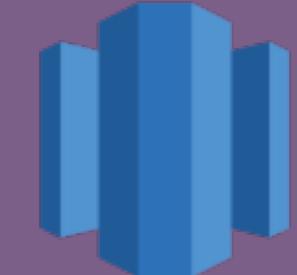
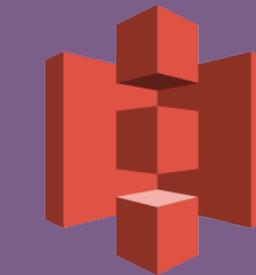
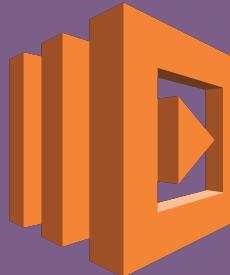
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MARKETING OPTIMIZATION AT SPOTHERO

DATA COLLECTION

Transaction data in AWS Redshift

User acquisition data: Google Analytics, etc
to Redshift via backend ETL or webhooks + AWS S3 + AWS Lambda



EXAMPLE

MARKETING OPTIMIZATION AT SPOTHERO

DATA QUERYING

Query Redshift using Psycopg2 into pandas dataframes



pandas
 $y_{it} = \beta' x_{it} + \mu_i + \epsilon_{it}$

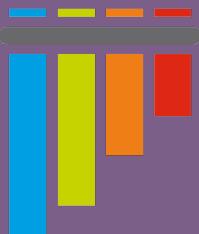


EXAMPLE

MARKETING OPTIMIZATION AT SPOTHERO

CHANNEL ATTRIBUTION

Assign likelihood for each customer that a marketing channel was used in their acquisition



pandas
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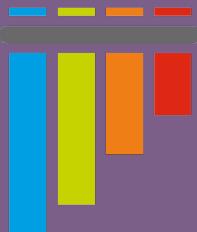
EXAMPLE

MARKETING OPTIMIZATION AT SPOTHERO

CHANNEL ATTRIBUTION

Assign likelihood for each customer that a marketing channel was used in their acquisition

Data factories for pytest unit tests



pandas
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EXAMPLE

MARKETING OPTIMIZATION AT SPOTHERO

ASSIGN COHORTS

Cluster users together, usually by month of acquisition, city, etc

pandas
 $y_{it} = \beta' x_{it} + \mu_i + \epsilon_{it}$



EXAMPLE

MARKETING OPTIMIZATION AT SPOTHERO

COHORT VALUE FORECASTS

Use historical trends to predict future revenue

pandas
 $y_{it} = \beta' x_{it} + \mu_i + \epsilon_{it}$



EXAMPLE

MARKETING OPTIMIZATION AT SPOTHERO

COHORT VALUE FORECASTS

Use historical trends to predict future revenue

Regression forecasting + attrition modeling + backtesting in scikit-learn

ARIMA forecasting + tests for autocorrelation, stationarity, etc in statsmodels



pandas
 $y_{it} = \beta' x_{it} + \mu_i + \epsilon_{it}$

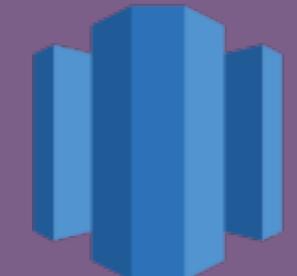
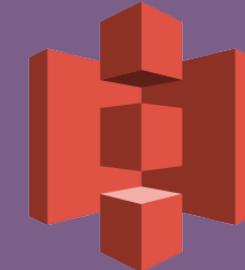
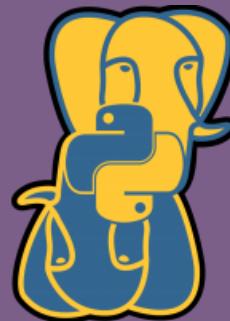


EXAMPLE

MARKETING OPTIMIZATION AT SPOTHERO

MARKETING SPEND

Move marketing spend csv to Redshift via S3 using Boto 3 + Psycopg2



EXAMPLE

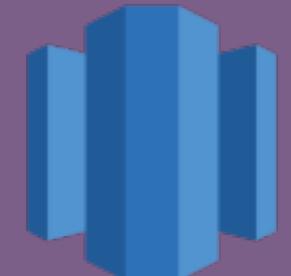
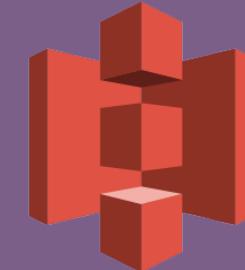
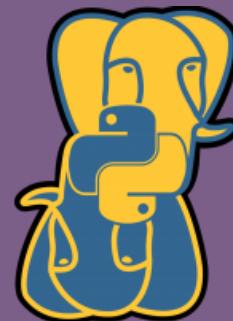
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Divvy spend to customers using algorithm in (you guessed it) pandas

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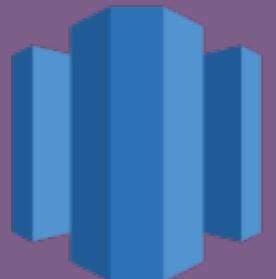


EXAMPLE

MARKETING OPTIMIZATION AT SPOTHERO

CAC/LTV RATIO OPTIMIZATION

Customer acquisition costs (CAC) and lifetime value (LTV) forecasts
are written to a data store in Redshift



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CAC/LTV RATIO OPTIMIZATION

Customer acquisition costs (CAC) and lifetime value (LTV) forecasts
are written to a data store in Redshift

Marketing analysts use this data in the Looker BI tool to find efficient channels

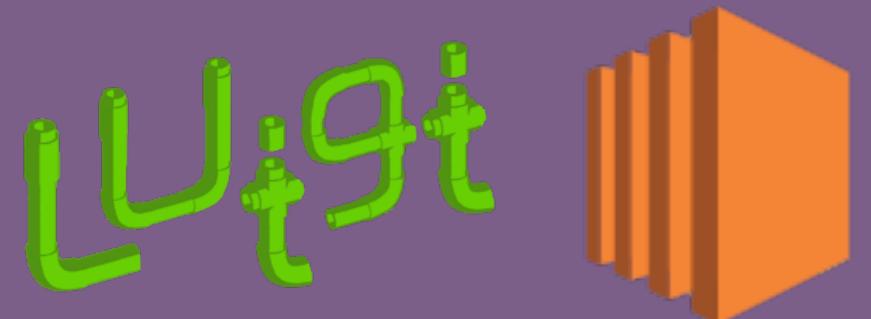


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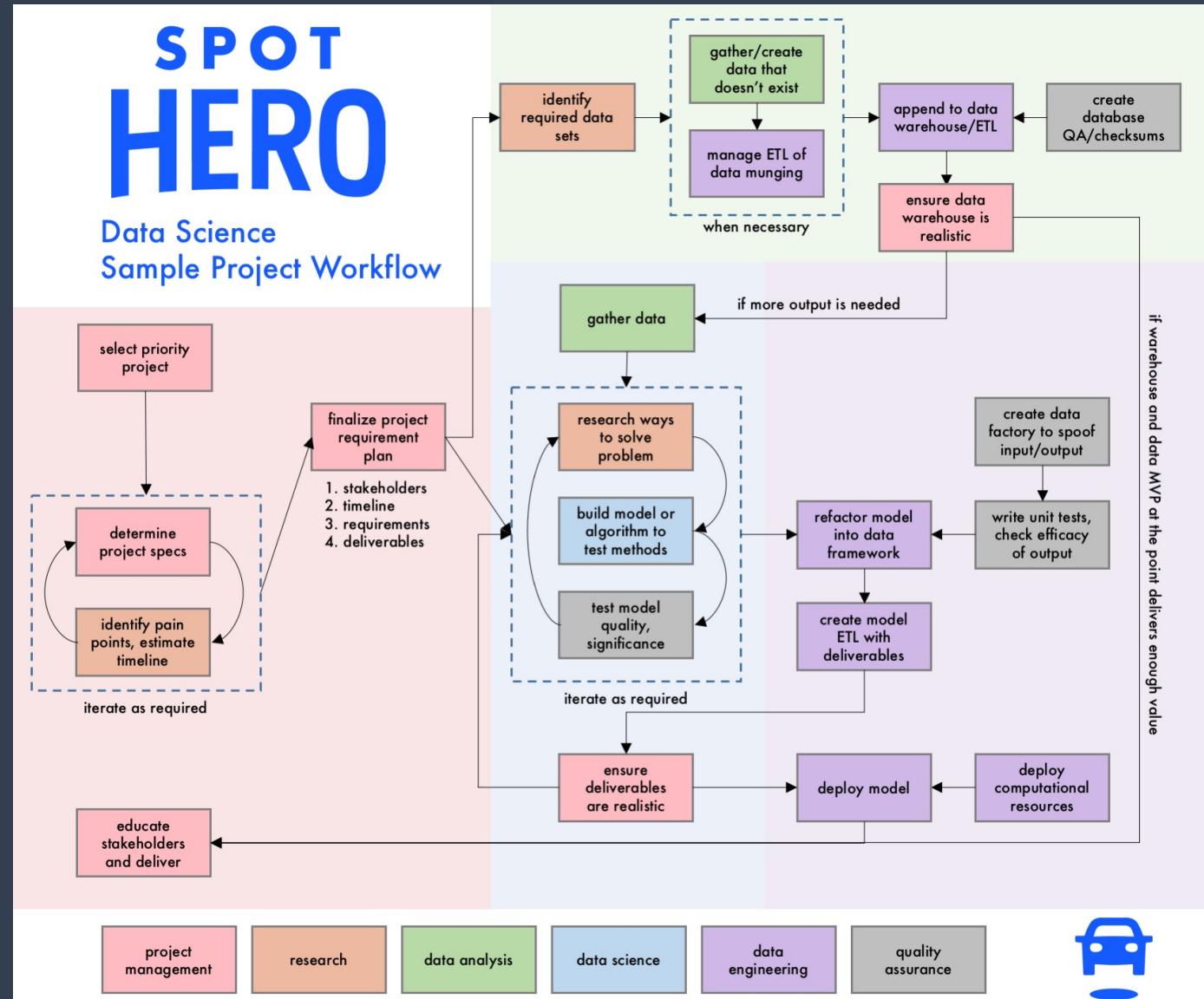
ETL PROCESS

Task dependencies on each branch of process handled by Luigi
on AWS EC2 instance



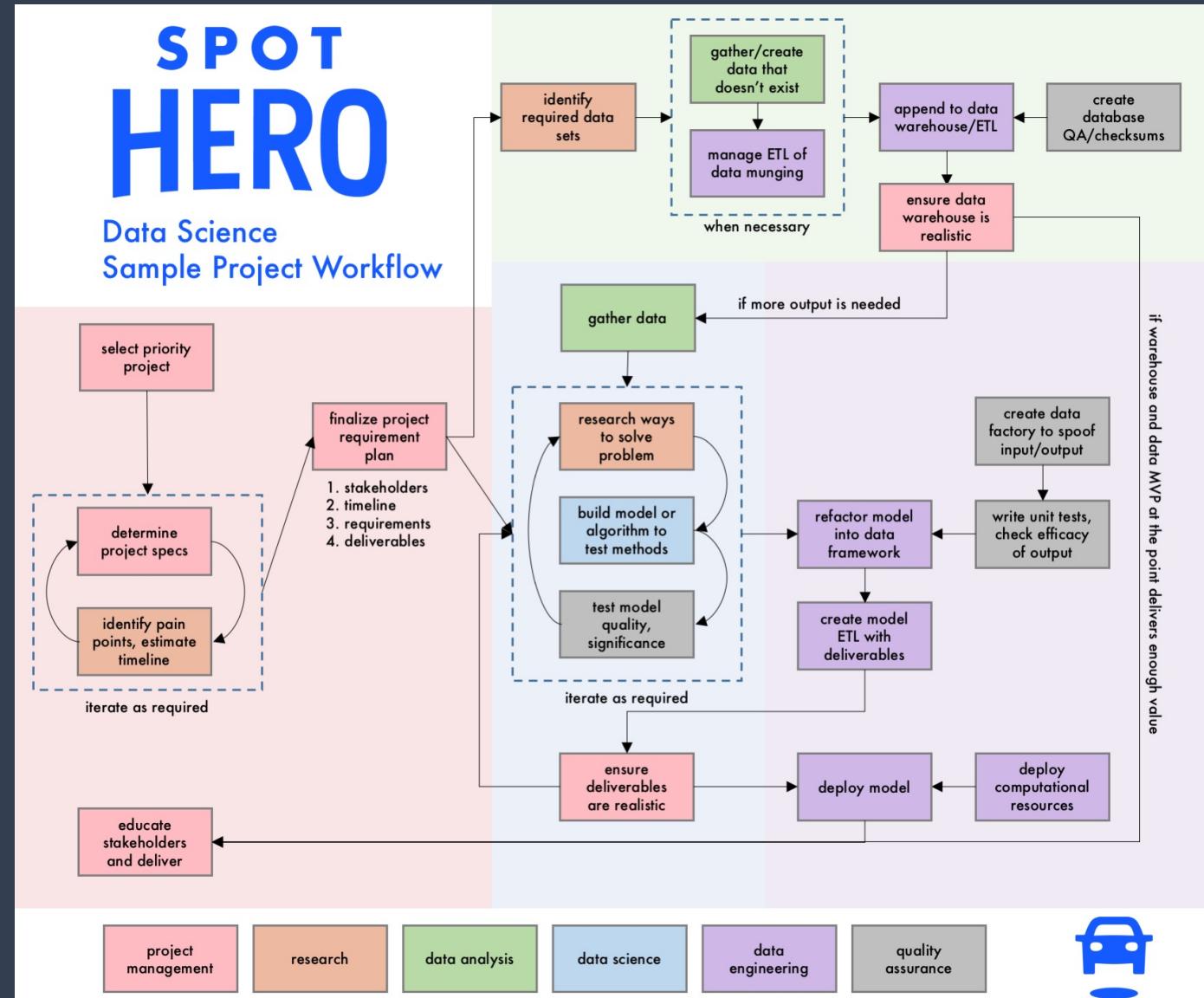
REMINDER:

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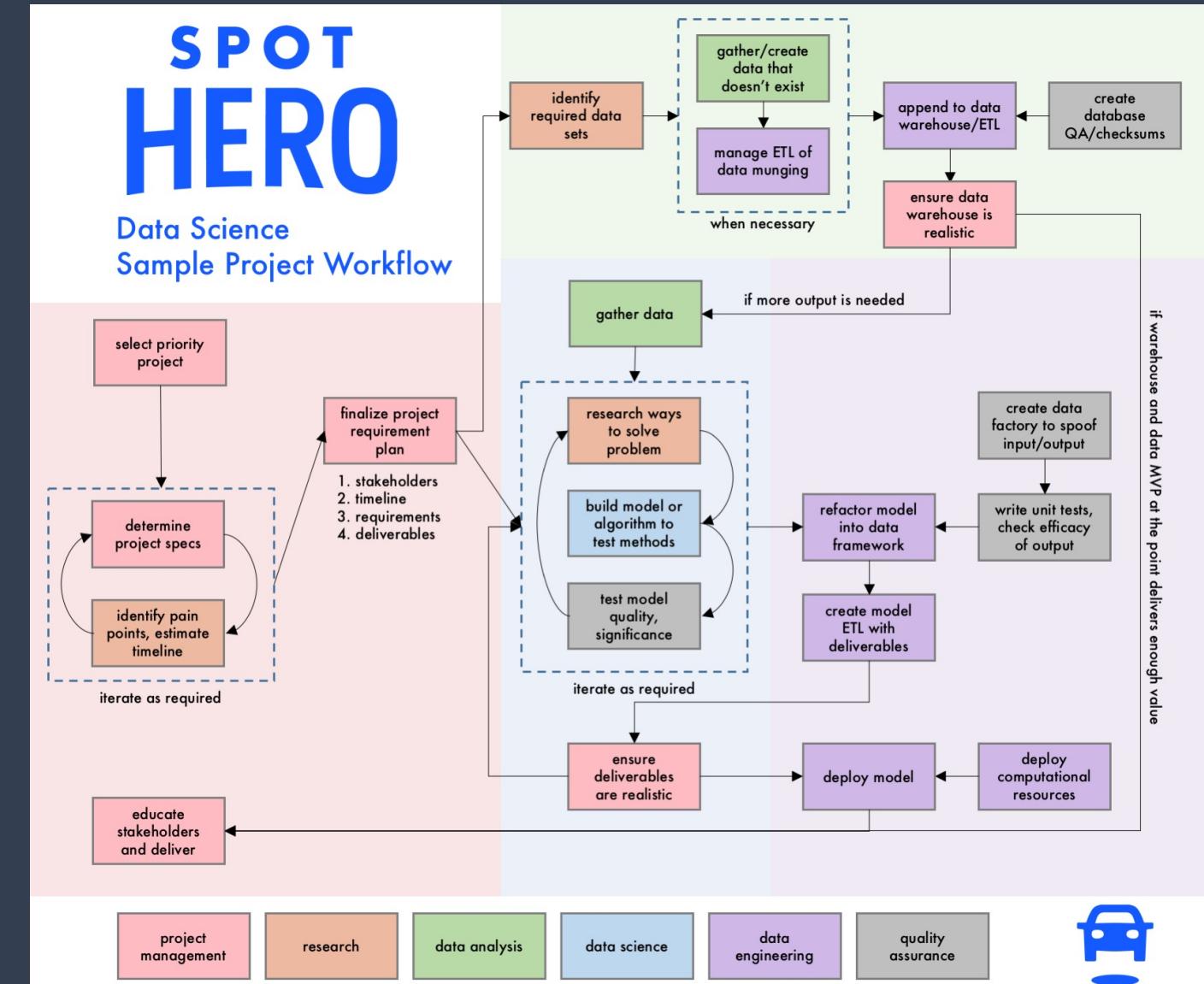
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TRY YOUR BEST TO BE YOUR OWN:
DATA SCIENTIST
DATA ENGINEER
QA TEST ENGINEER
PROJECT MANAGER
UX RESEARCHER



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FURTHER READING

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[Maxims for Modelers \[Arthur Geoffrion\]](#)

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[Highly Effective Data Science Teams \[Drew Harry\]](#)

<https://medium.com/mit-media-lab/highly-effective-data-science-teams-e90bb13bb709>

[Data Engineering Architecture at Simple \[Rob Story\]](#)

https://github.com/wrobstory/DataEngArchSimple/blob/master/2016_03_29_SimpleDataArch_with_notes.pdf

[Data Science Team-Building and Optimization \(talk\) \[Jeremy Stanley\]](#)

https://www.youtube.com/watch?v=CqQyrkEvh_8