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Agile Data Science
Achieving Salesforce-Scale Machine Learning in Production

Sarah Aerni, PhD
Director of Data Science, Einstein Platform
saerni@salesforce.com
@itweetsarah
ACM Highlights

• Learning Center tools for professional development: http://learning.acm.org
  • The Safari Learning Platform featuring the entire Safari collection of nearly 50,000 technical books, video courses, O’Reilly conference videos, learning paths, tutorials, case studies
  • 1,800+ Skillsoft courses, 4,800+ online books, and 30,000+ task-based short videos for software professionals covering programming, data management, DevOps, cybersecurity, networking, project management, and more; including training toward top vendor certifications such as AWS, CEH, Cisco, CISSP, CompTIA, Oracle, RedHat, PMI.
  • 1,200+ books from Elsevier on the ScienceDirect platform (including Morgan Kaufmann and Syngress titles)
  • TechTalks from thought leaders and top practitioners
  • Podcast interviews with innovators, entrepreneurs, and award winners

• Popular publications:
  • Flagship Communications of the ACM (CACM) magazine: http://cacm.acm.org
  • ACM Queue magazine for practitioners: http://queue.acm.org

• The ACM Code of Ethics, a set of principles and guidelines principles and guidelines designed to help computing professionals make ethically responsible decisions in professional practice: https://ethics.acm.org

ACM Digital Library, the world’s most comprehensive database of computing literature: http://dl.acm.org

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• And much more... http://www.acm.org.
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Talk Back

• Tweet your favorite quotes from today’s presentation with hashtag #ACMLearning

• Submit questions and comments via Twitter to @acmeducation – we’re reading them!

• The ACM Discourse Page is available for post-talk discussion – https://on.acm.org
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Statement under the Private Securities Litigation Reform Act of 1995:

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Different Flavors of AI and ML in Industry

Models that inform strategic decisions

Examples
- Data-driven drug discovery
- Risk models for investments

Models that are products

Examples
- Chatbots
- Algorithmic Trading

Models that augment products

Examples
- Predictive Lead Scoring
- Case Classification
Adoption of AI is Considered Critical to Stay Competitive!

**FIGURE 2**

**AI helps organizations keep up with the (Dow) Joneses**
Relative to competitors, respondents say their company’s adoption of AI has allowed them to...

- 16% Catch up
- 20% Stay on par
- 27% Edge slightly ahead
- 28% Widen a lead
- 9% Leapfrog ahead


Deloitte Insights | deloitte.com/insights
For the Majority of Businesses, Data Science is Out of Reach
Overall, 39% of Data Scientists and Advanced Analysts require a master’s or Ph.D. ... Therefore, because these roles are already undersupplied and projected to grow rapidly, the skills shortage is in danger of worsening.
Empowering Every Admin & Developer with AI
The Einstein platform

Out of the Box AI for Business Users
- Einstein for Commerce
- Einstein for Marketing
- Einstein for Service
- Einstein for Sales

Point-click Solutions for Admins
- Einstein Voice Assistant
- Einstein Next Best Action
- Einstein Bots
- Einstein Discovery

Einstein Platform Services for Developers
- Einstein Vision
  - Object Detection
  - Image Classification
  - Optical Character Recognition
- Einstein Language
  - Sentiment
  - Intent
  - Translation
- Einstein Predictions Service
- Einstein Predictions

NEW
- Einstein Predictions
- Einstein Language
- Einstein Vision
How we achieve Salesforce-scale!

Salesforce approach to democratizing AI

Enabling our customers to build models on their own data

The need for platform to ship AI to production

Bridging the communication gap between data scientists and software developers to find common ground and get to production and agility

Critical components of an AI platform

How to build a platform to support agile data science

How metrics drive agility and scale

How to apply agile methodologies to rapidly improve and deploy models
How Companies Build ML Apps

1. Business understanding
2. Data understanding
3. Data preparation
4. Modeling
5. Evaluation
6. Deployment

The process is cyclical, with data flowing through each step and feedback loops for continuous improvement.
How Companies Build ML Apps

Data Scientists on App #1

- Business understanding
- Data understanding
- Data preparation
- Modeling
- Deployment
- Evaluation

Data Scientists on App #2

- Business understanding
- Data understanding
- Data preparation
- Modeling
- Deployment
- Evaluation
Let’s Add a Third App

Data Scientists on App #1

Data Scientists on App #2

Data Scientists on App #3
How This Process Would Look in Salesforce

Customer #1

Customer #2

Customer #3

150,000 customers
There are varying degrees of skillsets
Different customers have different data sizes
Classification is not always classification
English is not the only language
Customers love to customize
AI needs to be trusted

Um, sure, I promise!
Can you hook me up to the internet now?

Super intelligent machines control strategies: teaching.
Fix your leaks

Thank you for your order!
ORDER CONFIRMATION FROM GODADDY.COM

Dear [Name],

This email contains important information regarding your recent GoDaddy.com purchase – please save it for reference. How did we do? Take our survey.

Customer Number: [Number]
Username: [Username]
Receipt Number: [Number]

Save 25%* off your next purchase of $75 or more

Save Now

USE PROMO CODE: GDBBA2228
Einstein’s New Approach to AI

Democratizing AI for Everyone

Classical Approach

- Data Sampling
- Feature Selection
- Model Selection
- Score Calibration
- Integrate to Application
- Artificial Intelligence

Einstein Auto-ML

- AI for CRM
  - Discover
  - Predict
  - Recommend
  - Automate

Data already prepped
Models automatically built
Predictions delivered in context
“MAKE EVERYTHING AS SIMPLE AS POSSIBLE, BUT NOT SIMPLER.”

ALBERT EINSTEIN
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A data scientist’s view of the journey to building models

- Explore Data
- Engineer Features
- Build Models
- Examine Results
- Model Goes Live
“The single biggest problem in communication is the illusion that it has taken place.”

- George Bernard Shaw
What are critical components to shipping your app!

**APPLICATION** to reach customers

**PIPELINES** to deliver data to *modeling* and *scoring* services

**MONITORS** to know the health of models

**EXPERIMENTATION** frameworks and **AGILE PROCESS** to iteratively improve

**WAY TO DEPLOY** new models

Source: Salesforce Customer Relationship Survey conducted 2014-2016 among 10,500+ customers randomly selected. Response sizes per question vary.
FIGURE 8

Companies need a broad range of skills for their AI initiatives
Respondents rating each a top-2 needed skill to fill their company’s AI skills gap

- AI researchers: 30%
- AI software developers: 28%
- Data scientists: 24%
- User experience designers: 23%
- Change management/transformation experts: 22%
- Project managers: 22%
- Business leaders to interpret AI results: 21%
- Subject-matter experts: 20%

Note: Base = those who said that their company has moderate/major/extreme skills gap in meeting the needs of AI/cognitive projects. Sample size = 752.

### How different are data scientist and software developers?

<table>
<thead>
<tr>
<th>Data Scientists</th>
<th>Software Developers</th>
</tr>
</thead>
<tbody>
<tr>
<td>Monitor the performance of their models</td>
<td>Monitor the performance of their apps</td>
</tr>
<tr>
<td>Identify opportunities to improve models</td>
<td>Identify opportunities to add features</td>
</tr>
<tr>
<td>Want to explore new data/algorithms</td>
<td>Want to explore new technology</td>
</tr>
<tr>
<td>Need processes to test new models</td>
<td>Need processes to test new features</td>
</tr>
<tr>
<td>Need a way to redeploy new models</td>
<td>Need a way to redeploy their app</td>
</tr>
<tr>
<td>Find opportunities for reuse</td>
<td>Find opportunities for reuse</td>
</tr>
</tbody>
</table>
Give your team the tools they need!
Supporting a Model in Production is Complex

Only a small fraction of real-world ML systems is composed of ML code, as shown by the small black box in the middle. The required surrounding infrastructure is fast and complex.

How we achieve Salesforce-scale!

Salesforce approach to democratizing AI
Enabling our customers to build models on their own data

The need for platform to ship AI to production
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How the Salesforce Einstein Platform Enables Data Scientists

Deploy, monitor and iterate on models in one location

Microservice architecture

Shared feature engineering and modeling services

Customizable model-evaluation & monitoring dashboards

In-platform secured experimentation and exploration

Data Scientists focus their efforts on engineering new features, trying new models and evaluating results

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How do we build models? evaluate? reuse?

```python
>>> from sklearn import svm
>>> from numpy import loadtxt as l, random as r
>>> clf = svm.SVC()
>>> pls = numpy.loadtxt("features.data", delimiter="",
                      testSet = r.choice(len(pls), int(len(pls)*.7), replace=False)
>>> X, y = pls[-testSet,:-1], pls[-testSet:-1]
>>> clf.fit(X,y)
SVC(C=1.0, cache_size=200, class_weight=None,
               coef0=0.0, decision_function_shape=None, degree=3,
               gamma='auto', kernel='rbf', max_iter=-1,
               probability=False, random_state=None, shrinking=True,
               tol=0.001, verbose=False)
>>> clf.score(pls[testSet,:-1], pls[testSet,-1])
0.88571428571428568
```
Learn from the mistakes of others. You can’t live long enough to make them all yourself.

-Eleanor Roosevelt
Introducing TransmogrifAI

Open Sourcing Auto-ML for Structured Data

Automated feature engineering, feature selection & model selection

ML abstractions that improve developer productivity & collaboration

Model explainability to improve debuggability and transparency

```
// Read the Deal data
val dealData = DataReaders.Simple.csvCase[Deal](path = pathToData).readDataset().toDF()

// Extract response and predictor Features
val (isClosed, predictors) = FeatureBuilder.fromDataFrame[RealNN](dealData, response =

// Automated feature engineering
val featureVector = predictors.transmogrify()

// Automated feature selection
val cleanFeatures = survived.sanityCheck(featureVector, removeBadFeatures = true)

// Automated model selection
val (pred, raw, prob) = BinaryClassificationModelSelector().
  setInput(isClosed, cleanFeatures).getOutput()
val model = new GpWorkflow().setInputDataset(dealData).setResultFeatures(pred).train()
```
Einstein’s New Approach to AI

Democratizing AI for Everyone

Classical Approach
- Data Sampling
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- Artificial Intelligence

Einstein Auto-ML
- AI for CRM
  - Discover
  - Predict
  - Recommend
  - Automate

Data already prepped
Models automatically built
Predictions delivered in context
### Repeatable Elements in Machine Learning Pipelines

AutoML for feature engineering

<table>
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<th>Categorical Variables</th>
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<td>John Gardner</td>
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<tr>
<td>Andy Smith</td>
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<td>Test User</td>
<td>um den heißen Brei herumreden</td>
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AI for CRM
- Discover
- Predict
- Recommend
- Automate
A tournament of models!

<table>
<thead>
<tr>
<th>CUSTOMER A</th>
<th>MODEL GENERATION</th>
<th>MODEL TESTING</th>
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<tr>
<td>Customer ID</td>
<td>Model 1</td>
<td>Model 1 83% accuracy</td>
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<td>Gender</td>
<td>Model 4 89% accuracy</td>
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<tr>
<td>Valid Address</td>
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- Customer ID: 1, 2, 3, 4, 5
- Age: 22, 30, 45, 23, 60
- Age Group: A, A, B, A, C
- Gender: M, F, F, M, M
- Valid Address: Y, N, N, Y, Y
A tournament of models!

CUSTOMER A

<table>
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CUSTOMER B

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</table>
How the Salesforce Einstein Platform Enables Data Scientists

Deploy, monitor and iterate on models in one location

Microservice architecture

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[Diagram showing various services and components like Lead Scoring, Case Classification, Engagement Scoring, and Prediction Builder, along with labels for configuration, data store, ETL/GDPR/Data Processing, machine learning, orchestration, model lifecycle management, and health monitoring.]
Monitoring your AI’s health like any other app component
Pipelines, Model Performance, Scores – Invest your time where it is needed!

105,874 Scores Written Per Hour (1 day moving avg)

0.86 Evaluation auROC

Sample Dashboard on Simulated Data
How we achieve Salesforce-scale!

Salesforce approach to democratizing AI

Enabling our customers to build models on their own data

The need for platform to ship AI to production

Bridging the communication gap between data scientists and software developers to find common ground and get to production and agility

Critical components of an AI platform

How to build a platform to support agile data science

How metrics drive agility and scale

How to apply agile methodologies to rapidly improve and deploy models
What happens after you deploy?
HOW TO BUILD A MINIMUM VIALBLE PRODUCT

NOT LIKE THIS

1. 😞
2. 😞
3. 😞
4. 😊

LIKE THIS

1. 😊
2. 😊
3. 😊
4. 😊
5. 😊

image by blog.fastmonkeys.com  original idea: spotify product team
Focusing on MVP with Agile Processes

HOW TO BUILD A MINIMUM Viable PRODUCT

Prioritized Backlog

- As a rider I want a comfortable seat so I can ride a longer time
- As a rider I want a self-powered vehicle so I can go further
- As a rider I want protection because I get hit by bugs
- As a rider I want shelter because I get wet when it rains
- As a rider I want to go faster so I can shorten my travel time

image by blog.fastmonkeys.com original idea: spotify product team
Focusing on MVP with Agile Processes

HOW TO BUILD A MINIMUM Viable PRODUCT

NOT LIKE THIS

☐ As a rider I want a comfortable seat so I can ride a longer time
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LIKE THIS
Focusing on MVP with Agile Processes

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HOW TO BUILD A MINIMUM Viable PRODUCT

NOT LIKE THIS

1
2
3
4

LIKE THIS

1
2
3
4
5

Image by blog.fastmonkeys.com original idea: spotify product team
Focusing on MVP with Agile Processes

Prioritized Backlog

- As a rider I want more room because I travel with 3 people
- As a rider I want protection because I get hit by bugs
- As a rider I want shelter because I get wet when it rains
- As a rider I want to go faster so I can shorten my travel time

As a rider I want a comfortable seat so I can ride longer distances

As a rider I want a self-powered vehicle so I can go further

HOW TO BUILD A MINIMUM VABLE PRODUCT

NOT LIKE THIS

1. Frowning
2. Frowning
3. Frowning
4. Smiling

LIKE THIS

1. Happy
2. Happy
3. Happy
4. Happy
5. Happy
Focusing on MVP with Agile Processes

Prioritized Backlog

- As a rider I want more room because I travel with 3 people
- As a rider I want to go faster so I can shorten my travel time

<table>
<thead>
<tr>
<th>Week 1</th>
<th>Week 2</th>
<th>Week 3</th>
<th>Week 4</th>
<th>Week 5</th>
<th>Week 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sprint 1</td>
<td>Sprint 2</td>
<td>Sprint 3</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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text by blog.fastmonkeys.com  original idea: spotify product team
Focusing on MVP with Agile Processes

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Focusing on MVP with Agile Processes

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- As a rider I want more room because I travel with 3 people

HOW TO BUILD A MINIMUM Viable PRODUCT

NOT LIKE THIS

1. Sad
2. Sad
3. Sad
4. Happy

LIKE THIS

1. Happy
2. Happy
3. Happy
4. Happy
5. Happy

image by blog.fastmonkeys.com  original idea: spotify product team
Iterative, Agile, MVP, PSPI, User Stories

WTH does this have to do with Models?

A data scientist’s view of the journey to building models

Explore Data

Engineer Features

Build Models

Examine Results

Model Goes Live
Iterative, Agile, MVP, PSPI, User Stories
WTH does this have to do with Models?
Endless choices for ways to improve!
“Le mieux est l'ennemi du bien”
(The best is the enemy of the good)

Voltaire
Invest your time where it is needed!
Pipelines, Model Performance, Scores – Monitors!

105,874 Scores Written Per Hour (1 day moving avg)

0.86 Evaluation auROC

Total Number of Scores Written Per Hour

Total Number of Scores Written Per Week

Distribution of Scores at Evaluation

Model Performance at Evaluation

Sample Dashboard on Simulated Data
Remember Our Scale at Salesforce

150,000 customers
WHERE DO WE SPEND OUR TIME?
WHERE DO WE SPEND OUR TIME?
## Deploy Monitors, Monitor, Repeat!

<table>
<thead>
<tr>
<th></th>
<th>Value</th>
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</thead>
<tbody>
<tr>
<td>Models in Production</td>
<td>134</td>
</tr>
<tr>
<td>Models Trained (curr.month)</td>
<td>215</td>
</tr>
<tr>
<td>Models with Above Chance</td>
<td>98.51%</td>
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<tr>
<td>Predictions Written Per Day</td>
<td>35,573,664</td>
</tr>
<tr>
<td>Experiments Run this Week</td>
<td>8</td>
</tr>
</tbody>
</table>

Sample Dashboard on Simulated Data
What is a sprint? What is a story? What is an investigation? How can agile work in Data Science?

Identify opportunity for improvement
Go live with model
Test for regression
Deep dive data to identify problem
Implement improvement
Run and review experiment

What should be shipped?
Creating tickets, user stories with clear acceptance criteria

**Investigation:**
Drop in auROC for model XYZ
AC: Deep dive of model and recent dataset, identify source of issues, create stories for follow-up fixes

**User Story:**
Add lead data object into model
AC: Engineer features from lead object, add to existing model, provide metrics to assess go-live

**User Story:**
Identify new hyperparameters settings for random forest
AC: Provide output of experiment with various settings, assess go-live

**SPIKE:**
Segmented models
AC: Design doc reviewed and approved by design board, follow-up stories created

**Bug:**
Blank text in field A not being treated as nulls
Creating your prioritized backlog: Value vs Ease of Implementation

Endless choices for ways to improve!
Deploy Monitors, Monitor, Repeat!

- **134** Models in Production
- **216** Models Trained (curr.month)
- **99.25%** Models with Above Chance Performance

| 12 Experiments Run this Week | 35,573,664 Predictions Written Per Day (7 day avg) |
Key Takeaways

• Plan for multiple apps... **always**
  Identify opportunities for reusability in all aspects, even your machine learning pipelines

• **Understand your data scientists**
  Build a platform to enable their productivity

• **Don’t fly blind**
  Make sure you can monitor your model health

• **Never deploy without a plan for iteration**
  How can your data scientist experiment?
  How can your data scientists redeploy?
  What will you do with your old predictions?
Go to github.com/salesforce/TransmogrifAI to learn more!
Introducing: New Einstein Services for Admins & Developers

Build custom AI you can trust

Einstein Platform Services:
Deploy NLP & Computer Vision inside of Salesforce using APEX Code or Lightning Web Components

Einstein Predictions Service:
Extend predictions outside of Salesforce into any external system like finance, HR, ERP & more

Trusted AI:
Ensure your AI is transparent, responsible & accountable
THANK YOU

@itweetsarah
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