From DBA to DE: Becoming a Data Engineer



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Who Am I, and What Am I Doing Here?







Liron Amitzi

Jim Czuprynski

The podcast that talks about everything tech – except tech.TM

https://www.beyondtechskills.com

What Does a Modern Oracle DBA Spend Her Time On?



Protecting database health, recoverability and security





Tuning queries for **optimal performance and efficiency**



Keeping data sources as pristine as possible to refresh data domains efficiently



Not Everyone Can Be A Data Scientist. Thank Goodness.



Data scientists report that they typically spend as much as **90%** of their time cleansing data ...



... and that's when they're not searching for relevant data, in numerous places, in different formats ...

... while ensuring their selected data is sufficiently anonymized to protect subjects' privacy



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What they'd <u>rather</u> be doing: Training models and interpreting results for useful insights

Data Science Is Just Like Application Development. (Not!)



DevOps: CI/CD Process Flow

- Focus: Capturing, retaining, and reporting on data
- Errors are relatively, if not immediately, apparent
- Worst case: Roll back to a prior version of the application and its objects within the database*

* Assuming you've planned for that eventuality!

Data Science: Data > Useful Model(s)

- Focus: Accurate (and thus useful) models
- Machine Learning / AI involves *extremely complex* mathematics that devour computing cycles
- Worst case: A perfect model is now **utterly inaccurate**!
 - Underfit: Poor *initial* training data results in bad model precisely when *it's most needed*
 - **Overfit:** Good *initial* training data yields a good model initially ... and then *new, never-before-seen* data screws up everything



Who Said AI/ML Was Easy?



Of course, it's more complicated than this. Check out my recent <u>blog post</u> for deeper insights



The Scourge of Bad Data (1)

BREAKING - 'WISCONSIN HOT' - Grassroots Group Uncovers 23,000 Votes with Same Phone Number and 8,000 Voters Registered in 1918 All In One County!

GATEWAY PUNDIT.

e report the truth — and leave the Russia-Collusion fairy tale to the Conspiracy media

Any decent clustering ML algorithm would likely produce findings like this when looking for unseen patterns within features

Trump was leading above

0.7

0.6

0.5

0.4

0.3

The reason for same dates? Values entered for birth date (1/1/00) and registration date (1/1/18) from some municipalities' voting records during conversion to a centralized voter registration system in 2002 And the duplicate phone numbers? They turned out to match a City of Racine office telephone number that had been entered by default because Racine's voting registration system required a non-NULL value



Vote Share

The Scourge of Bad Data (2)

An IT professional wanted to mess with California's Automatic License Plate Reader system ... so he registered his vanity plate as the word NULL

BRIAN BARRETT

SECURITY 00.13.2019 00:51 PM

How a 'NULL' License Plate Landed One Hacker in Ticket Hell

Security researcher Joseph Tartaro thought NULL would make a fun license plate. He's never been more wrong.

The next year, he got a \$35 ticket when he tried to renew his registration ... because NULL was no longer acceptable

After he paid the ticket, the 3rd party administrator of the ticket fines collection system apparently connected his personal details to **all plates which LEOs had registered as missing or invalid**

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\$12,000 in fines later, he realized the joke was on him

The Scourge of Bad Data (3)



Note: We haven't even talked about the concept of *gender* yet.



So What Does a DE Do, Exactly?





What Current DE Skills Do I Need?



Note: These are only *my* impressions of what skills are typically needed across a wide spectrum. So what skills do *your* Data Science team **really** need? Ask them.



How Do You Get To Carnegie Hall? Practice, Practice, Practice.



If you're still a "core" DBA, don't fret! You can start practicing all the skills you'll need to become a **Data Engineer**

> It's easy to **leverage** the extremely powerful **Machine Learning** (ML) algorithms and **Analytic functions** already within the Oracle database ...

> > ... because sometimes the <u>only</u> way to acquire the skills for a new career vector is to **read > learn > do > teach**

Check out the <u>newest and latest features</u> of Autonomous Database, including AutoML, OML4Py, OML4SQL, Property Graph support, and Graph Studio UI



Configuring Your OML Environment (1)

1

Request new ML User creation

2 Specify username, password, and details

ORACLE Cloud Infrastructure		۰ (D)
Autonomous Transaction Processing	Download Client Credentials (Wallet) Connections to Autonomous Transaction Processing use a secure connection. Your existing tools and applications will need to use this wallet file to connect to The ORACLE Machine Learning User Administration	Set Resource Management Rules O Set resource management rules to allocate CPUIIO shares to consumer groups and to cancel SQL statements based on their runtime and amount of IO.
Overview Activity	Create User	Create Cancel
Administration Development	s le P * Username	AIMINOOB
RECLONED	First Name	m
	U Last Name O * Email Address	czuprynski jczuprynski@zerodefectcomputing.com
		Generate password and email account details to user. User will be required to reset the password on first sign in.
	Password Confirm Password	



Leveraging DBMS_DATA_MINING (1)





... and choose from a number of available data mining examples and templates

Anomaly Detection	Association Rules	Attribute Importance	Classification Prediction M	Clustering
This notebook shows how to detect	Notebook to show the use of Asso	Notebook to identify key attributes	Example notebook to predict custo	This notebook shows how to identi
Author:	Author:	Author:	Author:	Author:
Date Added: 2/13/18 11:16 PM	Date Added: 2/13/18 11:16 PM	Date Added: 2/13/18 11:16 PM	Date Added: 2/13/18 11:16 PM	Date Added: 2/13/18 11:16 PM
Tags: 'Anomaly Detection' 'Machine	Tags: 'SQL' 'Associations' 'Rules' 'M	Tags: 'SQL' 'Attribute Importance' 'K	Tags: 'Classification' 'Prediction' 'De	Tags: 'Clustering' 'K-Means' 'Expect
	X 2 Likes Q 900 4 120	2 Likes Q 623 32 32	* 5 Likes	X 1 Likes Q 706 40
My First NotebookOracle Machine Learning exampleAuthor:Date Added: 2/13/18 11:16 PMTags: 'SQL' 'Data' 'Graph'★ 4 Likes	Regression This notebook shows how to predic Author: Date Added: 2/13/18 11:16 PM Tags: 'Regression' 'SVM' 'GLM' 'Logi * 1 Likes 993 \$ 35	Statistical Function Oracle Machine Learning example Author: Date Added: 2/13/18 11:16 PM Tags: 'Statistics' 'ANOVA' 'T-test' 'F 2 Likes Q 401 L 11	Time Series Forecasting Oracle Machine Learning supports Author: Date Added: 9/5/19 4:14 AM Tags: 'Prediction' 'Time Series' 'ESM' * 0 Likes • 158 • 5	

https://adb.us-ashburn-1.oraclecloud.com/oml/tenants/ocid1.tenancy.oc1_aaaaaaaa



AutoML: Let the Database Decide!

This makes it easier for "citizen data scientists" to apply the power of ML & Analytics ...

... the new AutoML interface makes selection of the proper algorithms a snap ...

... and many more new features, including Graph Studio

New Innovations in Oracle Autonomous Data Warehouse

The latest release includes many new innovations, not only a broad set of capabilities that make it easier for analysts, citizen data scientists, and line-of-business developers to take advantage of the industry's first and only self-driving cloud data warehouse, but also features that deliver deeper analytics and tighter data lake integration. Key capabilities include:

- Built-in Data Tools: Business analysts now have a simple, self-service environment for loading data and making it available to their extended team for collaboration. They can load and transform data from their laptop or the cloud by simply dragging and dropping. They can then automatically generate business models; quickly discover anomalies, outliers and hidden patterns in their data; and understand data dependencies and the impact of changes.
- Oracle Machine Learning AutoML UI: By automating time-intensive steps in the creation of machine learning models, the AutoML UI provides a no-code user interface for automated machine learning to increase data scientist productivity, improve model quality and enable even non-experts to leverage machine learning.

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What do you want to do with you	r data?		Getting Started
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Explore and Connect		Next	
IIII EXPLORE Impect data in your Autonomous Database	CLOUD LOCATIONS Manage connections to your cloud dorage (Davide, S3, Asure, Gangle)		
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Dracle Data Load	d		

Check out the <u>summary</u> of all the latest AutoML enhancements!



Building a Data Source for AutoML to Devour

We're drawing on

data summarized

from a Hybrid

Partitioned table

containing financial

statistics

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    , SM
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    , SM
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  FROM
                  THEN 1 ELSE 0
               END AS solar superuser
  • •
            FROM
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                                                     ... as well as customer
               ,t meter readings
           WHERE smr id = sm id
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           GROUP BY sm id
                                                    solar energy usage data
           ORDER BY sm id) SM
         WHERE SM.sm id = CF.cf id
           AND SM.sm id = CD.cd id
         ORDER BY sm id;
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Regression Experiments with AutoML(1)

Crea

Name * Solar Su Commer Regress Data Sou

Prediction Select

► Add

🔺 Fea

C→ Ref

No data



First, select an appropriate **data** source

2 AutoML automatically builds a list of potential **features** and their key **metrics**

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	CD_MINORITY_OWNED	CHAR	0	2					
	CD_YEARS_IN_BUSINESS	NUMBER	0	99	1	99	49.85	28.83	
	PCT_PROFIT_MARGIN	NUMBER	0	41	0.1	0.5	0.3	0.04	
	PCT_SOLAR	NUMBER	0	14	0.1	0.23	0.15	0.02	
	SM_ID	NUMBER	0	50067	1969787	2766834	2684098.22	64562.58	
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Regression Experiments with AutoML(2)





Start the experiment, choosing either **speed** or **accuracy**

ſ	🕨 Start 💌
	Faster Results
	Better Accuracy



Q

•

3

Review settings for prediction type, run time, model metric, and ML algorithms to apply

Regression Experiments with AutoML(3)



AutoML now 5

finishes any sampling needed and

moves on to

feature

selection

Regression Experiments with AutoML(4)

7

Model generation is complete! On to Feature Prediction Impact assessment ...

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Experiment Settings 🥒 Edit			Algorithm Selection Completed	0
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1.8 1.6			Feature Selection Completed	0
1.2 1.0			Model Tuning Completed	0
eader Board			Neural Network Completed	0
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Algorithm	Model Name	R2	Generalized Linear Model (Ridge	0
-		1 0000	Regression)	
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Regression Experiments with AutoML(5)

8

Regression(s) **complete**! Now let's transform the **Neural Network** model into a **Zeppelin notebook**, with *just a few mouse clicks*

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Transform an AutoML Experiment into a NoteBook (1)

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Solar SuperUser Regression		
🕨 Experiment Settings 🛛 🖋 Edit		2 Name the new notebook
R2		
1.0 0.8		Create Notebook ×
0.6 0.4 0.2	- 1	Create a notebook based on selected model and this experiment's settings. Use a generated notebook to further tune your approach using Python.
0.0		Notebook Name: SolarSuperUserRegression (NN)
Leader Board		OK Cancel
Deploy Create Notebook Metrics		
Algorithm	Model Name	gimr_2ta2ad7b18
Neural Network	nn_b512342ae0	-1 00500-735
Support Vector Machine (Gaussian)	svmg_014b2e6609	
Generalized Linear Model (Ridge Regression)	glmr_2fa2ad7b18	
Generalized Linear Model	glm_09f528c735	
Support Vector Machine (Linear)	svml_7226085a05	



Transform an AutoML Experiment into a NoteBook (2)



Don't know Python? No worries! The new notebook uses **OML4Py** to construct paragraphs for **data retrieval** and **modeling**

Transform an AutoML Experiment into a NoteBook (3)

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Build Data						FINISHED
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5

Et voila! Here's your first results from a notebook completely generated via *AutoML*!

How Do I Keep My DE Career Relevant?

How did you keep your Developer / DBA career relevant? How is this <u>any different</u>?

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Associate with other
 DEs, and help uplift
 others to DE status

 Attend conferences and training sessions on latest industry trends



 Consider certifying your hard-won, newly-acquired skills



They call it *life-long learning* for a reason - it **never**, <u>ever</u> stops!

Are There Any DE Professional Organizations? Maybe.





Further Reading In the Real World of Data Science

• Al Projects Fail All Too Often. Successful Ones Share a Common Secret

https://gestaltit.com/tech-talks/intel/intel-2021/jimthewhyguy/ai-projects-fail-all-too-often-successful-ones-share-a-common-secret/

- Machine Learning in Production: Why Is It So Hard and So Many Fail? https://towardsdatascience.com/machine-learning-in-production-why-is-it-so-difficult-28ce74bfc732
- Fact Check-Claims about 23,000 Wisconsin voters with the same phone number and 4,000 voters registered on 1/1/1918

https://www.reuters.com/article/factcheck-wisconsin-numbers/fact-check-claims-about-23000-wisconsin-voters-with-the-same-phonenumber-and-4000-voters-registered-on-1-1-1918-missing-context-idUSL1N2RU1WC

• How a 'NULL' License Plate Landed One Hacker in Ticket Hell

https://www.wired.com/story/null-license-plate-landed-one-hacker-ticket-hell/



Useful Oracle Documentation

• What is Data Science?

https://www.oracle.com/data-science/what-is-data-science/

• Machine Learning Solutions with Oracle's Services and Tools

https://www.oracle.com/a/ocom/docs/build-machine-learning-solutions-cloud-essentials.pdf

Oracle Cloud Infrastructure Data Catalog

https://www.oracle.com/a/ocom/docs/ebook-cloud-infrastructure-data-catalog.pdf

• OML Algorithms "Cheat Sheet"

https://www.oracle.com/a/tech/docs/oml4sql-algorithm-cheat-sheet.pdf

• Oracle 21c Machine Learning Basics (including AutoML)

https://docs.oracle.com/en/database/oracle/machine-learning/oml4sql/21/dmcon/machine-learning-basics.html

