Trends In Enterprise AI And Digital Decisions

September 18, 2019 – Bolzano Rules and Artificial Intelligence Summit

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I love AI
AI is a force for good.
It will make the world safer, healthcare more accessible, education personalized, manufacturing efficient, and will touch virtually every other aspect of humanity in net positive ways.
Enterprises must prioritize AI in order to be leaders in their industry.
Digital transformations must be powered by AI.
Customer experiences must be powered by AI.
Forrester projects that nearly every enterprise will use AI in five years.

“What are your firm's plans to use the following analytics technologies? (artificial intelligence)”

<table>
<thead>
<tr>
<th>Plan Description</th>
<th>2016</th>
<th>2017*</th>
<th>2018+</th>
</tr>
</thead>
<tbody>
<tr>
<td>Don't know</td>
<td>6%</td>
<td>7%</td>
<td>8%</td>
</tr>
<tr>
<td>Not interested/no plans</td>
<td>29%</td>
<td>23%</td>
<td>19%</td>
</tr>
<tr>
<td>Immediate</td>
<td>25%</td>
<td>20%</td>
<td>20%</td>
</tr>
<tr>
<td>Planning to implement within the next 12 months</td>
<td>40%</td>
<td>51%</td>
<td>53%</td>
</tr>
<tr>
<td>Implementing, implemented or expanding</td>
<td>51%</td>
<td>53%</td>
<td></td>
</tr>
</tbody>
</table>

Base: 2,094, 2,106*, 1,742 + data and analytics decision makers
Source: Forrester Analytics Global Business Technographics® Data And Analytics Survey, 2016, 2017, 2018
#Quiz
AI Quiz
How well do you know this customer?

› Male
› 35 years old
› Single
› Resides in New York City
› Makes $125,000 per year

What do you predict he would do if the bank accidently transferred $5,000 into his bank account?

A. Give the money back
B. Take the money and run

Please refrain from answering if you have taken this quiz before.
We humans excel at decision-making shortcuts when information is incomplete.

1. Anchoring bias
2. Availability heuristic
3. Bandwagon effect
4. Blind-spot bias
5. Choice-support bias
6. Clustering illusion
7. Confirmation bias
8. Conservatism bias
9. Information bias
10. Ostrich effect
11. Outcome bias
12. Overconfidence
13. Placebo effect
14. Pro-innovation bias
15. Recency
16. Salience
17. Selective perception
18. Stereotyping
19. Survivorship bias
20. Zero-risk bias
Decisions
How can we make the best possible digital decisions?
❤️ AI
Advice to implement enterprise AI successfully
Set high, but pragmatic expectations for AI
Forrester recognizes two types of AI: Pure and Pragmatic.
Pure AI strives to imitate comprehensive human intelligence…
AI researchers predict that Pure AI has a 50% chance of being achieved in 125 years.
Pragmatic AI often exceeds human intelligence for thousands of use cases.
Pragmatic AI is not one technology. It is comprised of one or more building block technologies.
Be pragmatic, not dramatic.
Leave no use case unexamined.
There are as many use cases as there are business processes and customer experiences.
Predict supply-chain issues while there is still time to remediate now.
Predict who will launch what cyberattack before it happens.
Predict experiments that are more likely to prove the hypothesis to avoid wasting time.
Predict imminent machine failure.
Predict benefits eligibility fraud.
Predict price movements to find investment opportunities before the market does.
Predict customer propensity to buy more with targeted offers.
There are thousands of use cases in today’s global enterprises.
Demystify machine learning for business people.
Machine learning algorithms analyze data to create predictive models.
Machine learning algorithms “train” a “model” that takes inputs to predict, decide, or identify.

\[ p = \text{model}(x, y, z, z', y') \]
Machine learning models can be very powerful and profitable, but understand that:

- Models are about probabilities, **NOT** absolutes
  - E.g. 78% chance you will enjoy watching *Money Heist* on Netflix

- Accurate models may **NOT** exist for every question
  - E.g. Elections, economic indicators, fashion, etc…

- Machine learning models are based on correlation and probably **NOT** causative
Correlation does not imply causation.
Data scientists and empowered business analysts explore data and develop machine learning models.
Data scientists use statistical and machine learning algorithms to build ML models.

Support vector machines (SVM)
Convolution networks
Last takeaway
Gradient boosting (GBM)
K-means
Feature selection
PCA
Kohonen Networks (SOFM)

Random forests
Mars regression splines
Linear and logistic regression
Naïve Bayes
Recurrent networks
The data science lifecycle is iterative and continuous.

Retraining on new data

Big data ingestion, processing and preparation

Model training using ML algorithms

Production

Model scoring/inferencing in applications

Development

Understanding

Integrate and enrich the data into an analytical data set

Prepare data

Run statistical and machine-learning algorithms to find the model

Model

Use the model in applications

Deploy

Test the model to make sure it will work

Evaluate

Identify data that is relevant to the business goal

Prepare data

Big data ingestion, processing and preparation

Model training using ML algorithms

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Test the model to make sure it will work

Evaluate

Identify data that is relevant to the business goal

Prepare data
Sell, sell, sweet ML.
Rethink tools for teams.
Data science needs software engineering discipline.
Predictive analytics & machine learning (PAML) solutions fall under three market segments.

- **Multi-modal**
  - Widest breadth of workbench tools

- **Notebook-based**
  - Code-first workbench for R, Python, etc

- **Automation-focused**
  - Designed specifically for automation
The Forrester Wave™: Multimodal Predictive Analytics And Machine Learning Solutions, Q3 2018

Widest breadth of workbench tools including visual UX, wizards, and programming
Forrester developed evaluation criteria from both buyer and vendor research

› Workbench
  • Data acquisition
  • Feature engineering
  • Modeling
  • Visualization
  • Collaboration
  • Automation

› Model operations
  • Model deployment
  • Model monitoring
  • Model staging
  • Ops collaboration

› Business solutions
  • Accelerators
  • Community

› Architecture
  • Scalability
  • Infrastructure

› Algorithms
  • Open source algorithms
  • Unique algorithms
**Forrester® RESEARCH**  
The Forrester Wave™  
**Multimodal Predictive Analytics And Machine Learning Solutions, Q3 2018**

by Mike Galtieri and Kjell Carlsson, Ph.D.

<table>
<thead>
<tr>
<th>Workbench</th>
<th>Dataiku</th>
<th>Datawatch</th>
<th>FICO</th>
<th>IBM</th>
<th>KNIME</th>
<th>MathWorks</th>
<th>Microsoft</th>
<th>RapidMiner</th>
<th>Seiford Systems (Minitab)</th>
<th>SAP</th>
<th>SAS</th>
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<td>Forrester's Overall Scores</td>
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### Control Level of Criteria Detail

- Less — More

### View scores with:

- Forrester's Weightings
- Your Custom Weightings

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<td>Model deployment</td>
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</table>
## Multimodal Predictive Analytics And Machine Learning

Q3 2018

by Mike Gualtieri and Kjell Carlsson, Ph.D.

### Control Level of Criteria Detail
- Less —○—○—○—○—More

<table>
<thead>
<tr>
<th>Evaluation Criteria</th>
<th>Criteria Explanation</th>
<th>Scale Explanation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Feature engineering</td>
<td>What capabilities exist to assist data scientists in feature engineering activities such as feature selection, feature creation, missing values, outliers, and other data preparation methods?</td>
<td>5 = Auto feature creation: Same as 3, plus the solution provides built-in feature selection/creation/dim-reduction capabilities and an automated variable selection/creation operator that does not require analysts to specify an explicit technique. 3 = Automated data prep: The solution has built-in data preparation capabilities that don't require analysts to specify an explicit technique (e.g., handling of categorical variables, missing values, outliers, normalization). 1 = Operators: The solution has a broad set of feature engineering capabilities that can be specified by the data scientist. 0 = The solution does not provide any automatic or semiautomatic data preparation/feature selection/creation/dim-reduction capabilities.</td>
</tr>
</tbody>
</table>

| Modeling            | What capabilities are available to allow data scientists to build custom pipelines to train and evaluate models, interface to another (e.g., it autogenerates a... | 5 = Ambidexterity: The solution provides an intuitive interface and advanced capabilities for building and managing custom data science pipelines that support collaboration and integration with other tools. 3 = Modular pipelines: The solution allows for the creation of modular pipelines that can be easily customized and reused across projects. 1 = Basic pipeline tools: The solution provides basic tools for building simple data science pipelines. 0 = No pipeline tools: The solution does not provide any tools for building data science pipelines. |
“Machine learning is an elemental core competency that every enterprise must have.”

“It is the electricity of artificial intelligence, the butterfly effect of the insights-driven business, and the chemical reaction of scalable intelligence across the enterprise.”
Predictive analytics & machine learning (PAML) solutions fall under three market segments:

- **Multi-modal**: Widest breadth of workbench tools
- **Notebook-based**: Code-first workbench for R, Python, etc
- **Automation-focused**: Designed specifically for automation
The Forrester Wave™: Notebook-based Predictive Analytics And Machine Learning Solutions, Q3 2018

Programming-first workbench for open source frameworks/libraries.
Forrester developed evaluation criteria from both buyer and vendor research

- **Platforms**
  - Notebooks
  - Management

- **Workbench**
  - Projects
  - Data Acquisition
  - Visualization
  - Collaboration
  - Automation
  - Open source algorithms

- **Model operations**
  - Model deployment
  - Model monitoring
  - Model staging
  - Ops collaboration

- **Architecture**
  - Scalability
  - Infrastructure

- **Business solutions**
  - Accelerators
  - Community
“Open source machine learning is evolving at a dizzying pace.”

“Driving outcomes with data science requires collaboration between teams, getting models into production quickly, and managing them at scale.”
Use tools to rule?
Insist on comprehensive access to enterprise data.
Garbage In = Garbage Out
Fortunately, global enterprises have thousands of sources of rich data.
Enterprise data is super rich as is needed for successful, pervasive AI

- Customer transaction data
- Point-of-sale data
- Customer and supplier contract data
- Inventory data
- Supply chain data
- Product/service data
- ERP and manufacturing data
- Supplier transactions
- R&D data
- Sales and CRM data
- Marketing/advertising data
- Human resources data
- Finance/accounting data
Data silos impede access to data…
…and, therefore dramatically slow the data science process.
Data scientists are often left begging for data.
Organize data engineering teams to optimize data science teams.
Option A: Data engineering teams deliver raw data

Data Engineering

Data Science

Best for: Enterprises that have limited data engineering resources.

Option B: Data science teams deliver raw data

Data source

Data source

Data source

Data source

Raw Data

Data Preparation

Feature Engineering

Modeling
Option C: Data engineering teams deliver pre-wrapped project data

Best for: Enterprises that have large teams working closely together.

Data Engineering

Data Acquisition

Data Preparation

Project Data

Data Science

Modeling

Feature Engineering

Option C: Data engineering teams deliver pre-wrapped project data

Best for: Enterprises that have large teams working closely together.
Algorithms get all the press, but it is the data that leads to success.
Know when to quit.
Machine learning is not guaranteed to work…
...that’s why you identify more than one potential use case.
If the data doesn’t fit, you must quit.
Use mathematical optimization to accelerate AI solutions.
Mathematical optimization (MO) determines the best decision based on real-world constraints.
AKA: decision optimization, mixed integer programming (MIP), linear programming (LP), optimization, constraint-based decisioning.
Mathematical optimization uses a solver to calculate the decision based on constraints.

\[ [d] = \text{solver}(o(), c^1(), c^2(), c^3(), \ldots) \]

- **Decisions**: optimal input variables that constitute the best decision
- **Mathematical optimizer**: software the calculates the best possible decision
- **Objective function**: defines a min or max that constitutes the best decision
- **Constraint functions**: defined by business requirements
Predict supply-chain issues while there is still time to remediate now.

Decide the least costly way to reroute shipments.
Predict who will launch what cyberattack before it happens.

Decide what investigators to assign to potential cyber threats based on investigator skill and potential damage.
Predict experiments that are more likely to prove the hypothesis to avoid wasting time right now.

Decide what experiments to pursue based on talent, cost, and time.
Predict imminent machine failure.

Decide when to shut the production line down to perform maintenance to minimize cost and customer complaints.
Predict benefits eligibility fraud.

Decide how to assign case workers to maximize recovery.
**Predict** price movements to find investment opportunities before the market does.

**Decide** how to allocate cash across all investment vehicles.
Predict customer propensity to buy more with targeted offers.

Decide how many discount coupons to offer to maximize revenue or to maximize profit.
ML predictions can determine the need to make a MO decision.
ML predictions can be used as MO decision constraints.
Use math to allocate cash?
Go faster with Auto-ML.
Data scientists aren’t expensive. They use inefficient tools.
Machine learning solutions fall under three market segments

- **Multimodal**
  - Widest breadth of workbench tools

- **Notebook-based**
  - Code-first workbench for R, Python, etc.

- **Automation-focused**
  - Designed specifically for automation
The ML model building lifecycle is highly iterative and continuous.

Retraining on new data

Model scoring/inferencing in applications

Big data ingestion, processing and preparation

Production

Model training using ML algorithms

Development

Identify data that is relevant to the business goal

Integrate and enrich the data into an analytical data set

Run statistical and machine-learning algorithms to find the model

Test the model to make sure it will work

Use the model in applications

Measure the effectiveness of the model in the real world

Deploy

Monitor

Prepare data

Model

Evaluate

Understand

ML models
Auto-ML solutions dramatically compress the model building lifecycle: feature engineering, algorithm selection, evaluation, and tuning.
Data-savvy users can build machine learning models for many business-worthy use cases.
Automated machine learning market landscape

AutoML-focused primarily for structured data

DataRobot
H2O.ai
dotData

AutoML primarily for deep learning

Microsoft
IBM
Google Cloud Platform

Multimodal ML with autoML

rapidminer
SAS

Automated insights

salesforce
outlier
empirical
AutoML automates the end-to-end machine learning lifecycle – data prep, feature engineering, model training, validation, and modelops.”
Forrester developed evaluation criteria from both buyer and vendor research

- User experience
- Data
- Feature engineering
- Methods
- Training
- Evaluation
- Model Operations

- Vision
- Roadmap
- Market approach
- Market presence
AutoML is quickly becoming a must-have for every organization looking to scale machine learning use.
Ring your bell with AutoML.
Operationalize models with ModelOps.
There are as many use cases as there are business processes and customer experiences.
Data scientists can build the models...
...and, application developers can infuse applications with AI models...
...but, ML models are probabilistic.
ML model performance can decay over time

- Positive Business Value
- Negative Business Value
- Time deployed

Maximum Business Value

= probabilistic model
Code is deterministic and always runs as written

Time deployed

Negative Business Value Positive

Code

= deterministic code
ML models must be monitored, retrained, and often remodeled.
Al models must stay in school to remain cool.
ModelOps is a repeatable, scalable process to stage, move, monitor, and govern model assets for production application consumption.
Stage models when necessary.
Move models to production.
Monitor models to make sure the models is performing, abiding, and doing no harm.
Collaborate with Devops and Ops.
Govern models to maintain lineage, explanations, auditability, and business outcomes.
No deploy, no joy.
Let AI help AI.
This machine can recognize speech.
This machine can wreck a nice beach.

This machine can recognize speech.
Combine multiple models to boost smartness.
Keep humans in the loop.
AI solutions are like us; they aren’t perfect.
Decision models encapsulate human-expressed decision processes.
Business rules are evaluated by an inferencing engine to abide by human-expressed knowledge.

\[ [a] = \text{decision}(r^1(), r^2(), r^3(), \ldots) \]

- **Actions**: Actions to take (or not) based on business rules
- **decision engine**: Software that evaluates the rules
- **Rules defined by human experts**
Black box machine learning models can rightly make executives and regulators nervous.
Are you sure?

Make the $1MM loan.
Are you sure?

Don’t make that loan.
You don’t have to do what the model tells you to do.
I shan’t.

Make the $1MM loan.
Pragmatic AI is smartest when driven by both humans and machines.
This is your perfect AI tech team

ML + MO + DD = AI
Rule your tools.
Eliminate infrastructure bottlenecks.
AI chips (GPUs and others) make deep learning possible...

**Central Processing Unit**
- Already present in AI Infrastructure; some have AI optimized instruction sets.
- Suitable for experimentation and modest training.

**Graphic Processing Unit**
- Hundreds of cores amenable to parallelize operations; ideal for training deep learning models.
- Existing support for popular deep learning frameworks like Tensorflow and MXNet.

**Field Programmable Gate Array**
- Programmable architecture ideal for inferencing on already trained models.
- Special software is required to translate trained model to the FPGA's configurable logic blocks.

**Application-Specific Integrated Circuit**
- Purpose-designed chip architectures to handle AI/deep learning training and/or inferencing workloads.
- Vendors who create these chips often label them as IPU, DPU, NNP, etc to reflect their design and branding.
...and, has created a resurgent, renaissance in integrated circuits and systems.

**AI Chips**
AI chips can massively parallelize operations amenable to AI model training and/or inferencing.

**AI Systems**
AI Systems include clusters of AI chips and additional high performance features such as fast interconnect and data access.

**AI Cloud**
AI cloud provides AI systems on-demand and therefore is instantly scalable.
ML models must be monitored, retrained, and often remodeled.

Business Value

Time deployed

Positive

Negative

Maximum Business Value

Model

= probabilistic model

Absolutely Retrain

Maybe Remodel

Negative Business Value

= model

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AI infrastructure used to train ML models must be available in perpetuity.
Big iron is back, baby.
Augment human intelligence.
Knowledge is hard to scale.
Employees struggle or fail to find the right answers.
Customers become frustrated trying to find answers.
Cognitive search is AI-powered search

- Keyword search
- Semantic search
- Contextual search
- Indexing
- Natural language processing (NLP)
- Machine learning
- Natural human interaction (NHI)

Future:
“Neural lace” (human brain merged with computers)
The Forrester Wave™: Cognitive Search, Q2 2019

“Employees and customers have an insatiable need for information. Cognitive search delivers it.”

“Top cognitive search vendors use more and varied AI technologies, such as natural language understanding (NLU), machine learning (ML), and deep learning.”
Forrester developed evaluation criteria from both buyer and vendor research

› Intelligence
  • Intent
  • Relevancy
  • Search
  • Tuning

› Information
  • Connectors
  • Ingestion

› Operations
  • Usage analytics
  • Tuning tools

› Security
  • Access
  • Certifications

› Architecture
  • Deployment
  • Scalability
  • Availability

› Applications
  • Pre-built applications
  • Custom applications
Forrester developed evaluation criteria from both buyer and vendor research

› Strategy
  • Ability execute
  • Solution roadmap
  • Pricing transparency
  • Customer service
  • Partners
  • Community

› Market presence
  • Customer adoption
  • Evaluated product revenue
  • Market awareness
Cognitive search unifies knowledge…
Cognitive search can make customer self-service a happy reality…
...and, employees polymaths.
To err is human; to augment, divine.
Imminent breakthroughs make the AI tools & technology market fluid.
Reinforcement learning (RL) learns by doing.
ML becomes creative with Generative Adversarial Networks (GANs) .
Deep learning will answer deeper questions with neuro-symbolic program induction.
Keep learning to stay young.
AI is the next age of human progress.
You will make it happen.
Thank you 😊

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