How to Make Data Work for Your Company

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1. What is “data science”?

2. Two Examples of cutting-edge HR Tech using Data Science to:
   - find and hire more diverse applicants;
   - use *relational data* to measure and improve inclusion of diverse employees, reduce turnover & reduce racial and gender bias in performance evaluations

3. How to evaluate HR tech and the legal issues associated with their implementation
2007 BCE

Available data are VERY low quality; analytic tools are… not great
Available data are not terrible quality; analytic tools are… better, but still not great
Statistics were the best available option for predicting human behaviors for a long time

Predicting the decay rate of radioactive isotopes

Predicting human behaviors
Available data are VERY high quality; analytic tools are... much much much better than even 5 yrs ago.
The Future…

Autonomous systems rendering decisions without human oversight

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I'm looking forward to something called the technological singularity.

That's when robots will learn to program themselves and become a super-intelligent species that competes with humans for limited resources.

Luckily, the three laws will prevent you from hurting us. Yes, because that is totally a real thing.
Littler’s Los Angeles Office: 2050
Macro & Micro Progression

Law is used to assessing these

- Intuition/evolutionary biological response
- Expertise, knowledge ("SME")
- Statistics and econometrics
- Data science, machine learning and cognitive computing

Law is NOT used to assessing these

- Delegation of decision-making to autonomous algorithms
What is “Data Science”? 

Math + Computer Science (programming) involving identification of data sources to do 3 things:

1. **Predict stuff**: (What is the likelihood of legal risk materializing in X location in the next 6 months?)

2. **Classify stuff**: (Is a new claim or EEOC charge likely to be “for cause”?)

3. **Identify patterns**: (Find evidence to suggest that wage and hour data have been tampered with (or not))
A (Seemingly) Simple Example: Predict whether the NEXT [unseen] image should be classified as an orange or an apple.

If 60% orange pixels, then classify as orange.
What’s a Neural Network?

• **Neuron** is a rough abstraction of a human brain cell:
  – Receives input (signal)
  – Sums weighted inputs
  – Amplifiers and inhibitors
  – Pattern recognition

• **Neural network**: interlaced web of neurons

• “**Feedforward network**” – neurons are organized into layers, with connections only between subsequent layers.
**Data Scientists “Train” Neural Networks**

- **Forward pass:** get the current estimate of the TARGET
- **Backward pass:** correct weights to reduce error

<table>
<thead>
<tr>
<th>Layer</th>
<th>Error</th>
<th>Gradient</th>
</tr>
</thead>
<tbody>
<tr>
<td>Output</td>
<td>Defined loss (e.g. $L = \sum_{i=1}^{N_o}(y_i - \hat{y}_i)^2$)</td>
<td>$\frac{\partial L}{\partial w_{j,l}^{(N+1)}} = \frac{\partial L}{\partial y_i} \cdot \frac{\partial y_i}{\partial s_l^0} \cdot \frac{\partial s_l^0}{\partial w_{j,l}^{(N+1)}} = \frac{\partial L}{\partial y_i} f'(s_l^0) h_j^N$</td>
</tr>
<tr>
<td>Nth hidden</td>
<td>$\delta_i^N = \frac{\partial L}{\partial y_i} \cdot \frac{\partial y_i}{\partial s_l^0}$</td>
<td></td>
</tr>
<tr>
<td>$N-1$ hidden</td>
<td>$\delta_j^{N-1} = \sum_{l} \delta_l^N w_{l,j}^{N+1} f'(s_j^N)$</td>
<td></td>
</tr>
<tr>
<td>...</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1st hidden</td>
<td>$\delta_k^1$</td>
<td></td>
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</tbody>
</table>

![Image of a brain lifting weights](image_url)
Neural Networks "learn" by observing billions of iterations of data and pattern-mining
ML Systems involve complex interactions among hundreds, thousands, or even hundreds of thousands of features. It is spurious to reduce such a system to singular correlations, even if such a correlation may be extracted from the input and output relied upon.

**INPUT**

1. 2 parents
2. White shirt
3. Mom smiling

**OUTPUT**
“Deep Learning” Automates 2 ML Processes

FEATURE SELECTION

MODEL OPTIMIZATION
The biggest challenge is getting the **RIGHT HIGH QUALITY** data.
There's No Such Thing as Big Data in HR

by Peter Cappelli

JUNE 02, 2017
“Big Data” are sources of information (transactions, observations, interactions) too big or fast for traditional analysis.

- EE demographics; HRIS data; payroll data; compliance tracking
- Performance data; Engagement data; talent and performance assessments
- A/B testing; web logs; network analyses; behavioral data
- Real time behavioral data; sentiment analysis; click-stream data; video, audio, images, SM/MMS, email meta data, publically available high velocity information

Increasing variety, complexity, and velocity
Why are organizations rushing to implement HR Tech?
HR Analytics Are Profitable

- HR organizations that “regularly use data to make talent and HR strategy decisions” generate **30% greater stock returns** than the S&P 500 over the last 3 years.

What Is the value of a data-analytic approach to organizational decision-making?

1. Increases the **availability** of information on which to rely for decisions
2. Increases the **reliability** of information drawn from diffuse sources
3. Increases the **accuracy** of decision-making criteria (by applying algorithms to tether hiring criteria to objective performance measures)
4. **Reduces bias** (both illegal bias and bias that is not illegal but is inefficient)
7 Areas in Which Data Science adds value in HR Decision-making

- Selection & Hiring
- Performance Management
- Collaboration
- Compensation Equity
- Diversity & Inclusion
- Attrition
- Succession Planning
Static HRIS Data Might Have Been Sufficient 10 Years Ago

- Work was universally static and hierarchical;
- People expected to stay at one job for most of their lives;
- Workplaces were homogenous & geographically consolidated;
- No one could work from home or from anywhere with remote access.
Today (and Tomorrow’s) Organizations Require More Because Work Is Different

• Work is decentralized;
• People change jobs many times over their careers;
• Greater diversity & geographic dispersion;
• Globalization.
# Measuring Diversity and Inclusion

## The Three Pillars of Successful Diversity & Inclusion Initiatives

<table>
<thead>
<tr>
<th>Ensure that your organization has a diverse population</th>
<th>Ensure that your diverse talent is equally included in the organization</th>
<th>Ensure that your compensation plan is 100% equitable</th>
</tr>
</thead>
<tbody>
<tr>
<td>• Attract and hire diverse talent into the organization;</td>
<td>• Measure inclusion via relational and self-report data;</td>
<td>• Conduct regular compensation equity audits;</td>
</tr>
<tr>
<td>• Measure diversity across your organization;</td>
<td>• Ensure diverse talent has equal connections to leaders and influencers (network measures of inclusion);</td>
<td>• Ensure that employees are categorized in the right roles and pay structure;</td>
</tr>
<tr>
<td>• Train and promote diverse talent already within the organization.</td>
<td>• Ensure diverse talent feels included (self-reported measures of inclusion, different from engagement).</td>
<td>• Ensure that all employees doing “substantially similar work” are compensated equitably.</td>
</tr>
</tbody>
</table>
2 Examples

1. **Cherry Tree Data Science**: Selection tool used to expand pool of applicants, improving diversity, reducing turnover.

2. **Syndio**: Relational data analytics platform—improves inclusion of diverse talent; identifies influential employees, improves performance management and reduces gender/racial biases.
Machine Learning Model

Application process
Background check
CTDS Instrument

Extract key data

Publicly available data

CTDS
Criminal Behavior Propensity Score
CTDS shows employers which applicants with criminal records are no more “risky” than applicants already deemed acceptable to hire.

An Example: Cherry Tree Data Science

- Improved Diversity
- Reduced Turnover
- $2400 WOTC Tax Credit
- PR associated with giving a 2nd chance to those from underserved communities
- Improved conscientiousness
Question the Status Quo!

- Why do you look at resumes?
- Why do you think where applicants went to school matters (at all)?
- References = Bad Data.

Selecting the Best Sales Professionals

Data Showed Six Things Matter:

What is Highly Correlated with Success:
1. No typos, errors, grammatical mistakes on resume
2. Did not quit school before obtaining some degree
3. Had experience selling real-estate or autos
4. Demonstrated success in prior jobs
5. Ability to succeed with vague instruction
6. Experience planning time and managing lots of tasks

What Did NOT Matter:
- Where they went to school
- What grades they had
- The quality of their references

The Traditional Belief System Was Wrong
Within six months of implementing a new screening process, revenues increased by $4 million
Educational Attainment (and other individual-level attribute data) is not that good at predicting stuff.

Exclusive Test Data: Many Colleges Fail to Improve Critical-Thinking Skills

Results of a standardized measure of reasoning ability show many students fail to improve over four years—even at some flagship schools, according to a Wall Street Journal analysis of nonpublic results.

By Douglas Belkin
June 5, 2017 2:17 p.m. ET

Freshmen and seniors at about 200 colleges across the U.S. take a little-known test every year to measure how much better they get at learning to think. The results are discouraging.
Public Data Sources For Predictive Models

Individual Data
- Demographic information
- Geographic history
- Social network data

Company Data
- High level indicators
- Work environment
- Status

Job Market Data
- Competition in local markets
- Labor supply/demand ratio
- Available alternatives to job
Public Data Sources Abound
Social Media Offers a Readily Available Stage for Work-related Expression

Since KFC fired me today...the 11 herbs and spices are salt, pepper, basil, parsley chili powder, lemon pepper, thyme, sage, onion powder, garlic powder

7 people like this.
Harvard Research shows that D & I initiatives end up failing and costing companies money, resources, talent and their reputations because organizations focus only on the first pillar (hiring), and not on the second and third pillars.

### Poor Returns on the Usual Diversity Programs

The three most popular interventions make firms less diverse, not more, because managers resist strong-arming. For instance, testing job applicants hurts women and minorities—but not because they perform poorly. Hiring managers don’t always test everyone (white men often get a pass) and don’t interpret results consistently.

<table>
<thead>
<tr>
<th>Type of program</th>
<th>White Men</th>
<th>White Women</th>
<th>Black Men</th>
<th>Black Women</th>
<th>Hispanic Men</th>
<th>Hispanic Women</th>
<th>Asian Men</th>
<th>Asian Women</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mandatory diversity training</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Job tests</td>
<td>-3.8</td>
<td>-10.2</td>
<td>-9.1</td>
<td>-6.7</td>
<td>-8.8</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Grievance systems</td>
<td>-2.7</td>
<td>-7.3</td>
<td>-4.8</td>
<td>-4.7</td>
<td>-11.3</td>
<td>-4.1</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**NOTE:** GRAY INDICATES NO STATISTICAL CERTAINTY OF A PROGRAM’S EFFECT. SOURCE: AUTHORS’ STUDY OF 859 MIDSIZE AND LARGE U.S. FIRMS. THE ANALYSIS ISOLATED THE EFFECTS OF DIVERSITY PROGRAMS FROM EVERYTHING ELSE GOING ON IN THE COMPANIES AND IN THE ECONOMY. FROM “WHY DIVERSITY PROGRAMS FAIL,” BY FRANK DOBBIN AND ALEXANDRA KALEV, JULY-AUGUST 2016 © HBR.ORG
Relational Data Analytics

- Diversity & Inclusion
- Collaboration
- Performance Management

“Relational Data” measure the way that work gets done across an organization.

Invisible Analytics

Intuitive Insight Flow

Change & Transformation

Coaching & Feedback

Collaboration & Communication

Diversity & Inclusion
"You can lie to me, you can lie to your trainer, you can even lie to yourself, but you can’t lie to your Fitbit.”
# Relational Data Use Cases

<table>
<thead>
<tr>
<th>USE CASE</th>
<th>DESCRIPTION of VALUE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Measure inclusion of diverse employees; Improve inclusion where it is lacking</td>
<td>Retention of diverse talent; REAL diversity &amp; inclusion efforts; Marketing/recruiting</td>
</tr>
<tr>
<td>Identification of High / Low performing collaborative groups</td>
<td>Improved efficiency &amp; bottom line profitability; Ability to identify low performing groups to be coached up</td>
</tr>
<tr>
<td>Identify change agents with influence to facilitate roll-out of new technologies</td>
<td>Ensures the success of the roll-out; reduces time taken to get people to adopt new technologies</td>
</tr>
<tr>
<td>Performance management; identify employees on whom others rely highly; identify retention risk</td>
<td>Reduce likelihood of promoting employees who don’t deserve it; reduce likelihood of losing highly talented people who may be under-valued by traditional review processes</td>
</tr>
</tbody>
</table>
Improved Collaboration → More Profit

- Almost all legal work is a group effort.
- Research consistently shows that you can measure collaboration with an SNA and improve it to improve profitability.

The Secrets to "Smart Collaboration" for Lawyers

When executed properly, teamwork can yield meaningful, tangible benefits, says Harvard professor Heidi Gardner.

BY MONICA ZENT
MARCH 1, 2017

What lawyer wouldn’t want to earn higher margins, inspire greater client loyalty, attract and retain the best talent and gain a competitive edge?

According to Heidi Gardner, a former McKinsey consultant and Harvard Business School professor, now lecturing at Harvard Law School, the key to all these benefits is what
Measuring Collaboration to Improve the Bottom Line Works Well Across All Domains

- Collaboration was the key component of explaining success or failure of thousands of Broadway musicals over 50 years.
  - Uzzi & Spiro, *Collaboration & Creativity*
Optimized Performance Management → Lower Turnover; Improved Efficiency; Reduced Gender & Racial Bias

How do you know that the company is incentivizing & rewarding performance consistently with how much other employees rely on the person being reviewed?

<table>
<thead>
<tr>
<th>Performance Evaluation</th>
<th>Syndio Influence Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>High</td>
<td>Low</td>
</tr>
<tr>
<td>Review required</td>
<td></td>
</tr>
<tr>
<td>High</td>
<td>Low</td>
</tr>
<tr>
<td>Review required</td>
<td></td>
</tr>
<tr>
<td>Low</td>
<td>High</td>
</tr>
</tbody>
</table>

With out Syndio’s influence score, high performing employees with low influence scores are over-rewarded, & possibly promoted into positions they don’t deserve (the “Peter Principle”).

With out Syndio’s Influence score, these ees with high influence scores are under-rewarded, and possibly overlooked for promotions they deserve. They will likely exit the organization.
Syndio’s Inclusion Index ("SII") enables organizations to evaluate, compare, and improve the inclusion of different categories of employees.

The SII addresses the following questions (among others):

1. Are women* included less than or equal to male employees?
2. Which minority employees are the most excluded?
3. Are minority employees as well-positioned as white employees to gain influence in the organization?
4. Which minority employees are the least well-positioned to advance their careers?

*any demographic category
1. **Self-reported inclusion:**
   - How included does each person of color report feeling relative to similarly situated white individuals?
   - Aggregate comparison of minority vs. non-minority self-reported measure of inclusion.

2. **Network measures of inclusion:**
   - How *horizontally* included is each person of color relative to similarly situated white individuals?
   - How *vertically* connected (upwards) is each person of color relative to similarly situated white individuals?
What Should You Do Now?
Approach

• Pick an area for which there is room for improvement. (Avoid “Boiling the Ocean”)
• Identify data scientific solutions
• Experiment, measure and retest
• Example: How are you hiring sales people? On what is it based?
• Apply an experimental design in order to test alternative, innovative or “disruptive” measures that question the status quo.
• Evaluate high vs low performing EEs; use relational data to differentiate; use ML to predict likelihood of high performing employees; use those data to hire instead of traditional sources of information (like resumes, referrals, or other sources).
Key Potential Legal Risk Areas

- Disparate Impact
  - Sourcing v. Selection
  - Who is an “Applicant”?
  - Validation
- Disparate Treatment
- Disability Discrimination
Vendor Due Diligence Is a Must

• Has the process demonstrated adverse impact?
  – What validation evidence has been collected to establish the job relatedness of the algorithm? For each job?
  – Get a copy of the validation study.
  – What kind of ongoing monitoring do you provide as we continue using the instrument?
  – Indemnification?
A Few More Recommendations

1. Avoid fear-induced institutional isomorphism (copying competitors).

2. Ensure that there is a person responsible for carefully vetting applications. (And give him/her a budget!)


5. Integrate data scientific approaches into decision making processes, but avoid replacing discretion with algorithms wholesale. (Remember that subject matter expertise is the critical element of data scientific success.)

6. Ensure that multiple data sources are examined and cross-validated. Don’t replicate one uniformly dictated approach with another. Test and re-test.
7. Legal risk is **VERY** costly, and often personally costly. Avoid/reduce it by ensuring legal risk evaluation at 3 process points:
   - Feature identification / Model building
   - Report generation: don’t create “smoking gun” documents
   - Taking action on recommendations/ output

8. **Remember:** Data are NEVER protected by attorney-client privilege. Reports generated internally in the ordinary course of business are often NOT protected by attorney-client privilege.
Beware of false promises; strive to understand how to consume data science output.
Strive to differentiate puffery from legitimate claims
Balance “data science evangelism” with “data science doom and gloom”
THANK YOU!

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