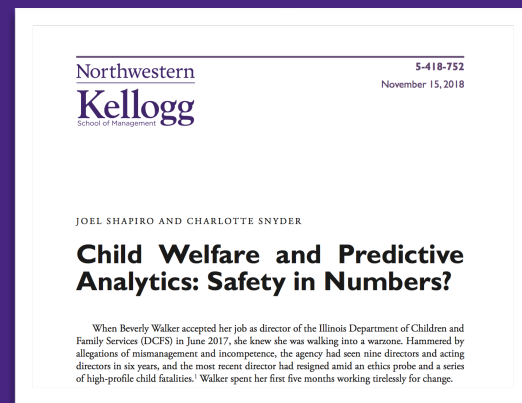
Safety in Numbers?

Case Discussion


Northwestern Kellogg
School of Management

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JOEL SHAPIRO AND CHARLOTTE SNYDER

Child Welfare and Predictive Analytics: Safety in Numbers?

When Beverly Walker accepted her job as director of the Illinois Department of Children and Family Services (DCFS) in June 2017, she knew she was walking into a warzone. Hammered by allegations of mismanagement and incompetence, the agency had seen nine directors and acting directors in six years, and the most recent director had resigned amid an ethics probe and a series of high-profile child fatalities.[1] Walker spent her first five months working tirelessly for change.

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When Beverly Walker accepted her job as director of the Illinois Department of Children and Family Services (DCFS) in June 2017, she knew she was walking into a warzone. Hammered by allegations of mismanagement and incompetence, the agency had seen nine directors and acting directors in six years, and the most recent director had resigned amid an ethics probe and a series of high-profile child fatalities.[1] Walker spent her first five months working tirelessly for change.

DISCUSSION IN SMALL GROUPS FIRST

12 min

1. How well does the predictive analytics tool match the needs of DCFS? Is this the right tool for the job? Or is this a mismatch in some way?

2. What about DCFS' org structure / staffing lends itself to success or failure with a predictive analytics tool? Where is there (mis-)alignment? For instance, what if DCFS had regular and significant turnover in case workers who use the predictive tool - would that make success more or less likely? What if they had low turnover?

3. What are the different ways that the predictive model might be right or wrong? Specifically, what do true/false positive/negatives look like here? How do false positives and false negatives affect deployment of resources, and what are the implications of being wrong?

QUESTION 1

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Success with analytics requires a clear problem that you are trying to solve or question that you are trying to answer.

Analytics can help direct limited resources by targeting at-risk kids. Seems like a solution that is appropriately tied to the problem here. All good.

QUESTION 2

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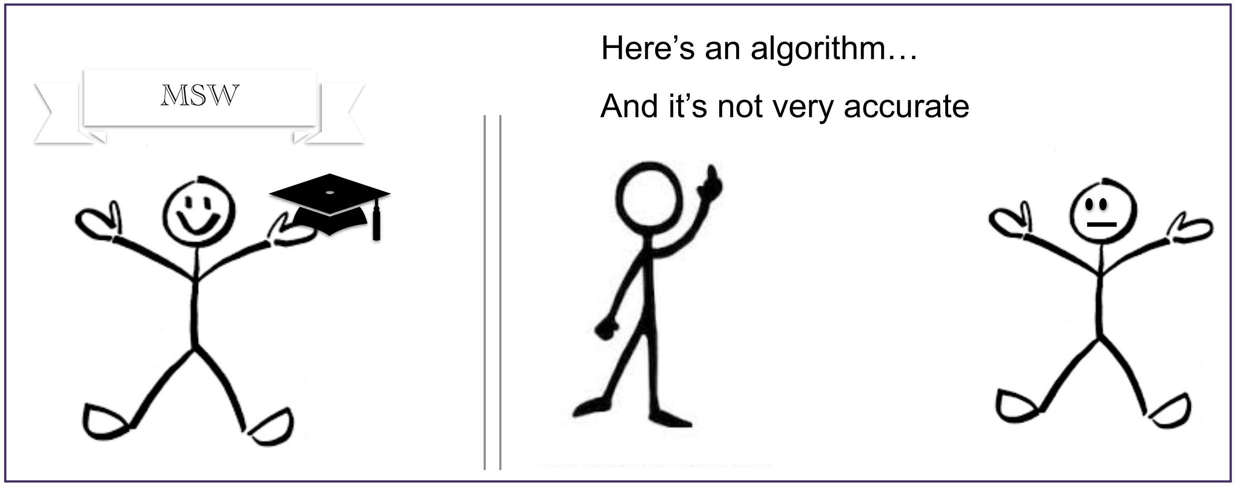
Potentially some problems here:

1. Leader of org doesn't understand predictive modeling, but "owns it." And it's really expensive
2. Front-line workers might not want it or know how to use it, and leader isn't supporting it.



QUESTION 2

What about DCFS' structure and staffing lends itself to success or failure with a predictive analytics tool?

(For instance, how might high staff turnover rates interact with the use of a predictive model?)

Either buy-in from the front line is required, or a leader needs to mandate that the tool will be used as a regular business practice.

Buy-in is challenging in an environment when even a great model has no monetary payoff. Funding a given tool means funding less of something else, and they're already in a resource-starved environment.

QUESTION 3

What is the preferred tradeoff between false positives and false negatives for DCFS?

How would FPs and FNs affect deployment of resources, and what is the implication of being wrong? How does this compare to, say, a company predicting whether customers will churn?

QUESTION 3

Data Scientists care about
Confusion Matrix

Predicted

		-	+
Actual	-	TN	FP
	+	FN	TP

DATA SCIENCE

Business Leaders care about
Payoff Matrix

Predicted

		-	+
Actual	-	$Benefit	$Cost
	+	$Cost	$Benefit

BUSINESS DECISIONS

QUESTION 3

What is the preferred tradeoff between false positives and false negatives for DCFS?

How would FPs and FNs affect deployment of resources, and what is the implication of being wrong? How does this compare to, say, a company predicting whether customers will churn?

After 2 high-profile and tragic false negatives, DCFS director says: “Predictive Analytics wasn’t predicting any of the bad cases.”

Questions to consider:

- If false negatives are so bad, what could you do to get rid of them?
- There were 2 deaths with model. How many would there have been without the model?

DISCUSSION IN SMALL GROUPS FIRST

12 min

4. The predictive model can identify kids who are at risk and enable DCFS to deploy resources to reduce that risk. How does risk mitigation differ in this context from, say, one where a company is trying to reduce risk of customer churn? For instance, imagine the following customer retention example:
   - Customer A is 100% likely to churn
   - Customer B is 10% likely to churn
   - You have an intervention that will reduce risk by 10 pp, but you only have the resources to use it for one customer. That is, Customer A to 90% OR Customer B to 0%. Which would you choose / why?

   Now use the same parameters, but change “customers / risk of churn” to “children / risk of abuse and death.” Would you intervene with A or B? Is your answer the same across contexts? SHOULD it be? Why / why not?

5. Do you think Beverly Walker was correct in getting rid of the predictive tool? What would you have done in her situation?

QUESTION 4: CHURN MANAGEMENT

STATUS QUO	OPTIONS	
$p(\text{churn})_{\text{cust1}} = 1.0$	$p(\text{churn})_{\text{cust1}} = 0.9$	$p(\text{churn})_{\text{cust1}} = 1.0$
$p(\text{churn})_{\text{cust2}} = 0.1$	$p(\text{churn})_{\text{cust2}} = 0.1$	$p(\text{churn})_{\text{cust2}} = 0$

QUESTION 4: CHURN MANAGEMENT

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On average, how many customers will you lose / keep?	Here?	Here?
If each has the same CLV, what is the expected value?	Here?	Here?

QUESTION 4: CHURN MANAGEMENT

STATUS QUO	OPTIONS	
$p(\text{churn})_{\text{cust1}} = 1.0$	$p(\text{churn})_{\text{cust1}} = 0.9$	$p(\text{churn})_{\text{cust1}} = 1.0$
$p(\text{churn})_{\text{cust2}} = 0.1$	$p(\text{churn})_{\text{cust2}} = 0.1$	$p(\text{churn})_{\text{cust2}} = 0$
Expected loss = 1.1	**Expected loss = 1.0**	**Expected loss = 1.0**
Expected retention = 0.9	**Expected retention = 1.0**	**Expected retention = 1.0**
Expected value = 0.9*CLV	**Expected value = 1.0*CLV**	**Expected value = 1.0*CLV**

QUESTION 4: CHURN MANAGEMENT

These are equivalent, as long as our goal is "minimize total loss, or maximize total retention, or maximize total value."

STATUS QUO	OPTIONS	
$p(\text{churn})_{cust1} = 1.0$	$p(\text{churn})_{cust1} = 0.9$	$p(\text{churn})_{cust1} = 1.0$
$p(\text{churn})_{cust2} = 0.1$	$p(\text{churn})_{cust2} = 0.1$	$p(\text{churn})_{cust2} = 0$
Expected loss = 1.1	**Expected loss = 1.0**	**Expected loss = 1.0**
Expected retention = 0.9	**Expected retention = 1.0**	**Expected retention = 1.0**
Expected value = 0.9*CLV	**Expected value = 1.0*CLV**	**Expected value = 1.0*CLV**

QUESTION 4: SAVING KIDS

STATUS QUO

$p(\text{death})_{\text{child1}} = 1.0$

$p(\text{death})_{\text{child2}} = 0.1$

On average, how many children will you keep alive?

If each child has the same value, what is the expected value?

OPTIONS

Option 1	Option 2
$p(\text{death})_{\text{child1}} = 0.9$	$p(\text{death})_{\text{child1}} = 1.0$
$p(\text{death})_{\text{child2}} = 0.1$	$p(\text{death})_{\text{child2}} = 0$
Here?	Here?
Here?	Here?

QUESTION 4: SAVING KIDS

But here, are these really equivalent?

STATUS QUO	OPTIONS	
$p(\text{death})_{\text{child1}} = 1.0$ $p(\text{death})_{\text{child2}} = 0.1$	$p(\text{death})_{\text{child1}} = 0.9$ $p(\text{death})_{\text{child2}} = 0.1$	$p(\text{death})_{\text{child1}} = 1.0$ $p(\text{death})_{\text{child2}} = 0$
Expected deaths = 1.1 **Expected lives = 0.9** **Expected value = 0.9*CLV**	**Expected deaths = 1.0** **Expected lives = 1.0** **Expected value = 1.0*CLV**	**Expected deaths = 1.0** **Expected lives = 1.0** **Expected value = 1.0*CLV**

SAME NUMBERS AS BEFORE!

QUESTION 4: SAVING KIDS

"I can't tolerate knowing that a child will die when I could have done something to possibly save them."

STATUS QUO	OPTIONS	
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$p(\text{death})_{\text{child2}} = 0.1$	$p(\text{death})_{\text{child2}} = 0.1$	$p(\text{death})_{\text{child2}} = 0$
Expected deaths = 1.1	**Expected deaths = 1.0**	**Expected deaths = 1.0**
Expected lives = 0.9	**Expected lives = 1.0**	**Expected lives = 1.0**
Expected value = 0.9*CLV	**Expected value = 1.0*CLV**	**Expected value = 1.0*CLV**

QUESTION 4: SAVING KIDS

STATUS QUO

$p(\text{death})_{\text{child1}} = 1.0$

$p(\text{death})_{\text{child2}} = 0.1$

OPTIONS

$p(\text{death})_{\text{child1}} = 0.9$

$p(\text{death})_{\text{child2}} = 0.1$

p(both die) =

p(exactly 1 dies) =

p(neither dies) =

$p(\text{death})_{\text{child1}} = 1.0$

$p(\text{death})_{\text{child2}} = 0$

p(both die) =

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QUESTION 4: SAVING KIDS

STATUS QUO	OPTIONS	
$p(\text{death})_{\text{child1}} = 1.0$ $p(\text{death})_{\text{child2}} = 0.1$	$p(\text{death})_{\text{child1}} = 0.9$ $p(\text{death})_{\text{child2}} = 0.1$ p(both die) = 0.09 p(exactly 1 dies) = 0.82 p(neither dies) = 0.09	$p(\text{death})_{\text{child1}} = 1.0$ $p(\text{death})_{\text{child2}} = 0$ p(both die) = 0 p(exactly 1 dies) = 1.0 p(neither dies) = 0

QUESTION 4: SAVING KIDS

STATUS QUO	OPTIONS	
$p(\text{death})_{\text{child1}} = 1.0$	$p(\text{death})_{\text{child1}} = 0.9$	$p(\text{death})_{\text{child1}} = 1.0$
$p(\text{death})_{\text{child2}} = 0.1$	$p(\text{death})_{\text{child2}} = 0.1$	$p(\text{death})_{\text{child2}} = 0$
	✓	
	p(both die) = 0.09	p(both die) = 0
	p(exactly 1 dies) = 0.82	p(exactly 1 dies) = 1.0
	p(neither dies) = 0.09	**p(neither dies) = 0**

If our goal is to maximize chances that neither dies, there is a preferred choice.

QUESTION 4: SAVING KIDS

STATUS QUO

$p(\text{death})_{\text{child1}} = 1.0$

$p(\text{death})_{\text{child2}} = 0.1$

OPTIONS

$p(\text{death})_{\text{child1}} = 0.9$

$p(\text{death})_{\text{child2}} = 0.1$

p(both die) = 0.09

p(exactly 1 dies) = 0.82

p(neither dies) = 0.09

$p(\text{death})_{\text{child1}} = 1.0$

$p(\text{death})_{\text{child2}} = 0$

✓

p(both die) = 0

p(exactly 1 dies) = 1.0

p(neither dies) = 0

If our goal is to minimize chances that both die, there is a preferred choice.

SAVING CUSTOMERS

SAVING KIDS

For analytics to work well, we not only need a well-defined business problem, but we must be explicit about what we are trying to accomplish - that is, our **objective function**.

And **objective functions** can vary greatly across contexts.

Clarity on the objective function is what allows us to embed our **morals** and our **ethics** and our **philosophies** into our decision-making with data.

Here, revenue maximization is NOT the same as welfare maximization.
You know this at a gut level, but it's also defensible from a "math" perspective.

THE INTERSECTION OF ANALYTICS AND HUMANITARIANISM

I have met more than one social service / social impact non-profit leader who has dismissed analytics to help provide service, claiming something like:

"People are people, not data. Our goal is to be <u>human-driven</u> and <u>heart-driven</u>, not <u>data driven</u>."

But these are NOT opposites.

THE INTERSECTION OF ANALYTICS AND HUMANITARIANISM

Analytics can be a wonderful and powerful tool to identify and help those in need!

- Vulnerable kids
- Stroke victims
- Those in need of mental health services
- Victims of climate change / severe weather events
- Those whose jobs are likely to disappear

If we can predict who will be in need, we can do a better job of changing their environments OR getting them resources before they suffer harm.

But, analytics works best with a well-specified criterion for allocation of those resources. Without that specificity, analytics output becomes irrelevant.

QUESTION 5

What do you think the Executive Director should have done?

Chicago Tribune

Data mining program designed to predict child abuse proves unreliable, DCFS says

“We are not doing the predictive analytics because it didn’t seem to be predicting much.”

DCFS Director

TAKEAWAYS

- Analytics success requires a good match of tool to need
- Analytics success requires an org that can accept help from a “heartless algorithm”
- Analytics success requires acceptance of false positives AND false negatives and a plan for both
- Analytics success requires clear articulation of objective

= Analytics-savvy business leadership

Lessons are robust to enterprise: government / NGO / non-profit / for-profit

A Counter Example of a Solid Success

Allegheny County (Pittsburgh, PA)

NYTimes Mag: “Can an Algorithm Tell When Kids are in Danger?” 01-02-18