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Conference on Artificial
Intelligence

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VANCOUVER CONVENTION CENTRE – WEST BUILDING



Continual Causality Bridge

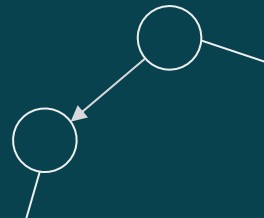


Causality Tutorial

Matej Zečević



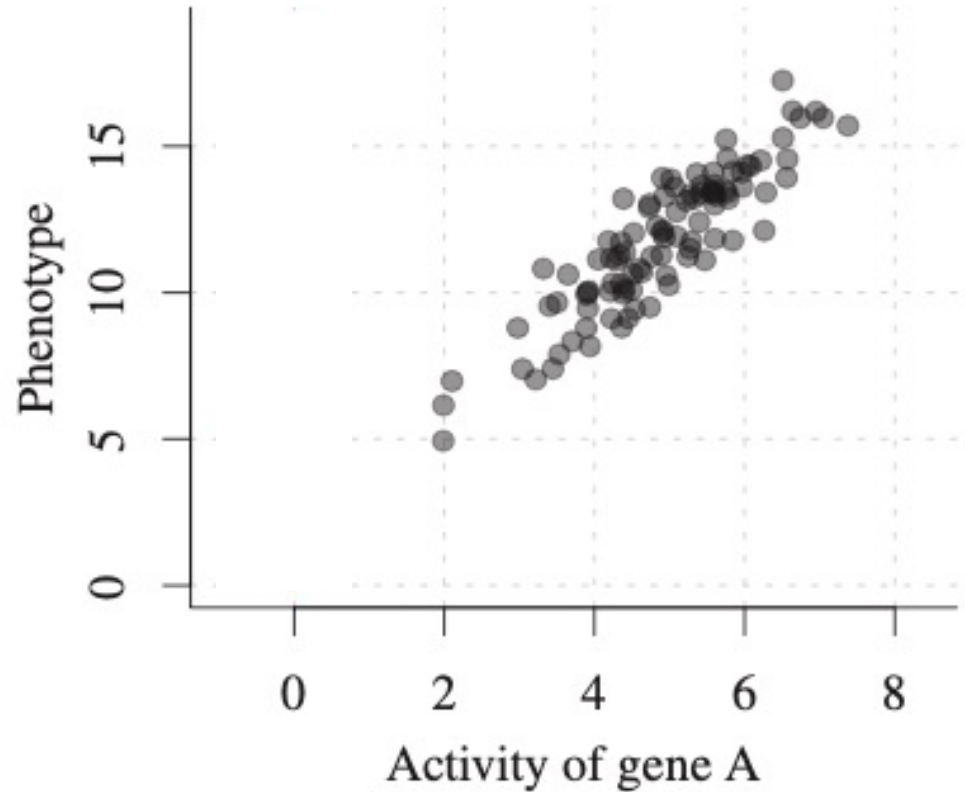
TECHNISCHE
UNIVERSITÄT
DARMSTADT



Why do we care
about causality
in AI & ML?

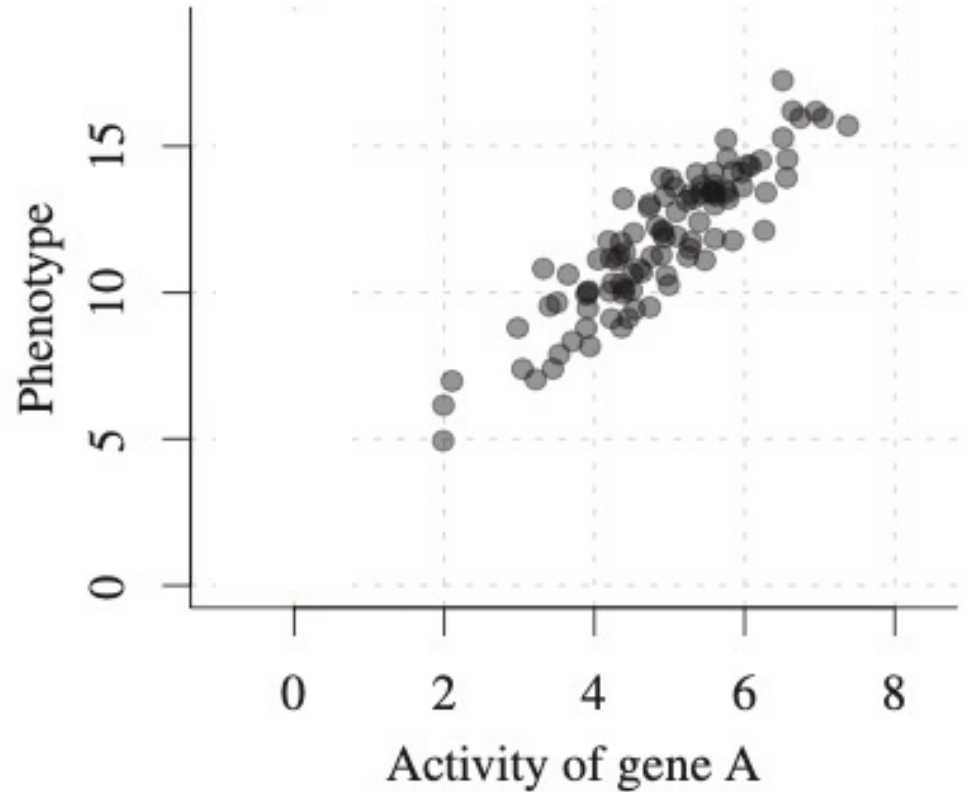
Example

Pharma gives you
a data set, telling
you they want to
be able to predict
phenotype
expression



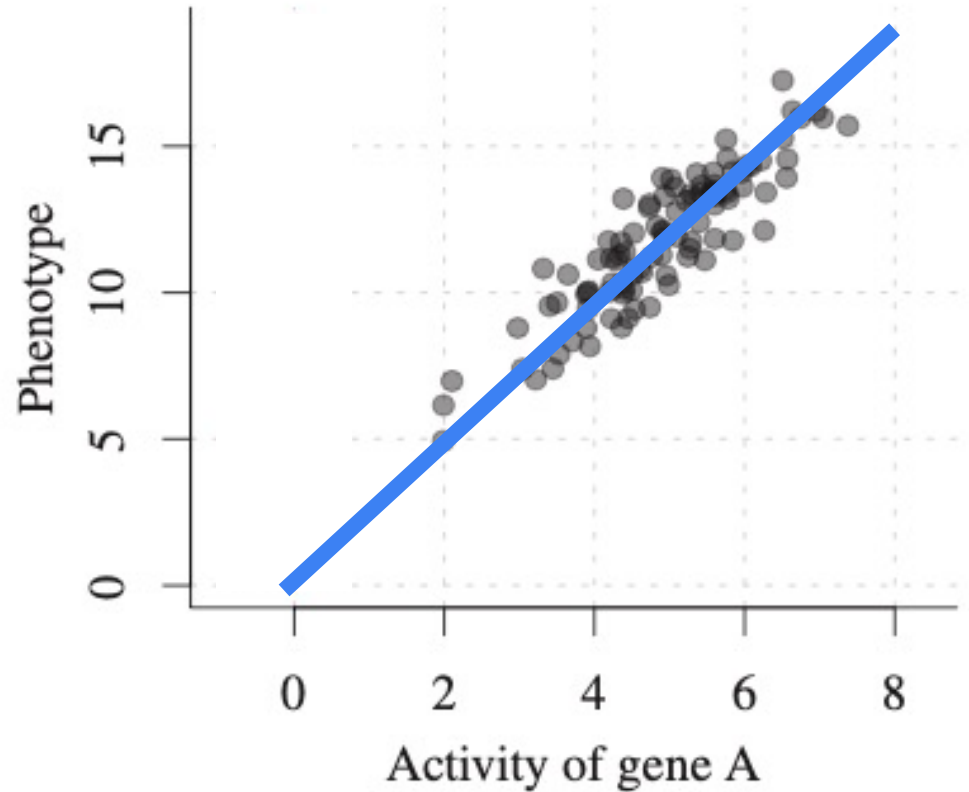
My question to
you:

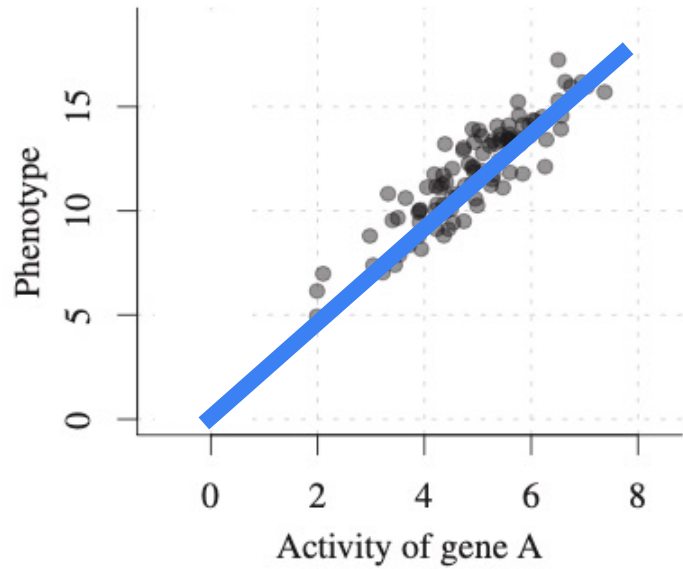
“How would
you do it?”



Learn a **Model**

Model learns a
linear function





Pharma is really
happy now, since,
wow, they have
full control now

Now they know things like:

Phenotype = 5 at Activity = 2,

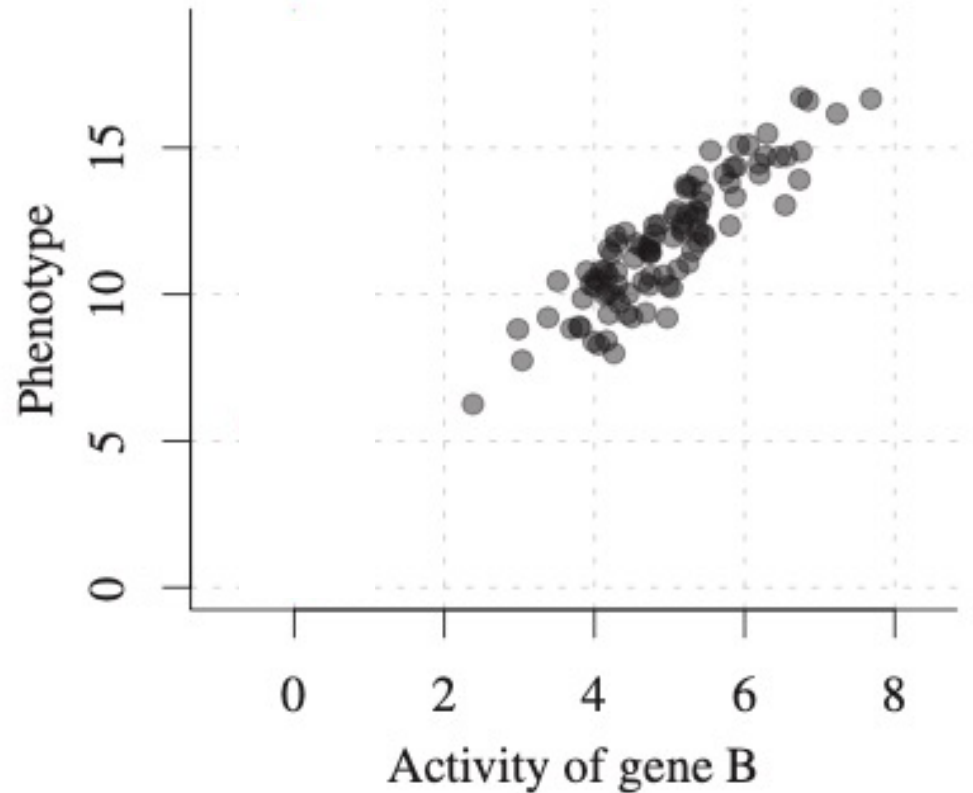
Phenotype = 15.8 at Activity = 6.1, or

Phenotype = 0 at Activity = 0

You're hired!

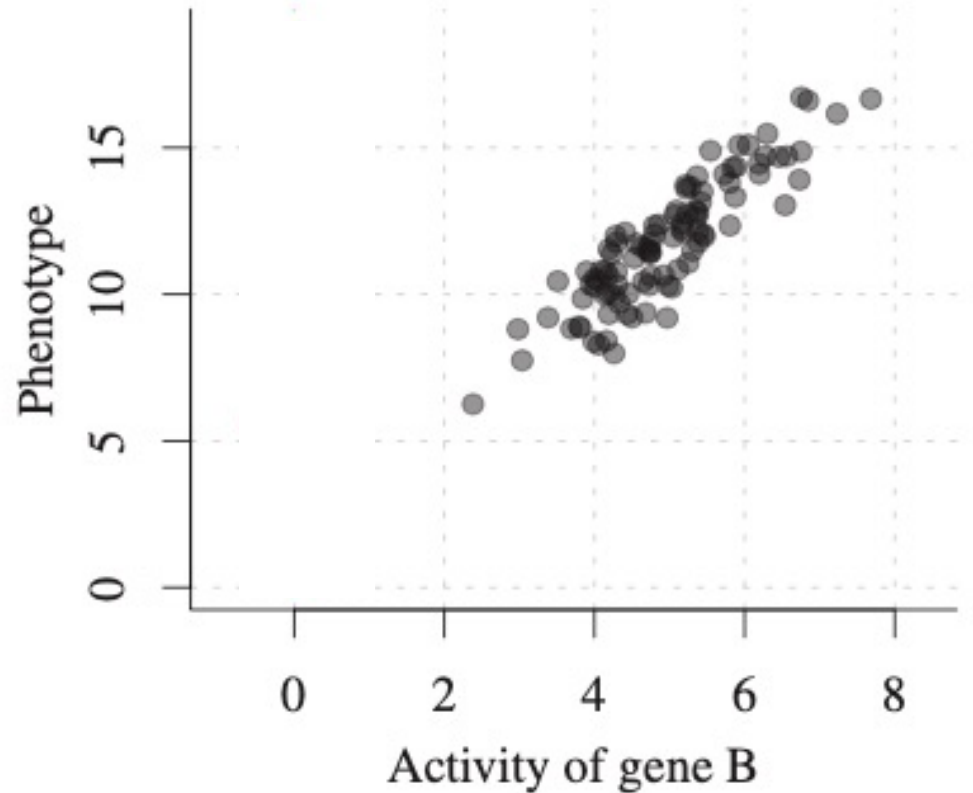
Example

Pharma has more
for you!
Another data set.
Same game,
different data set



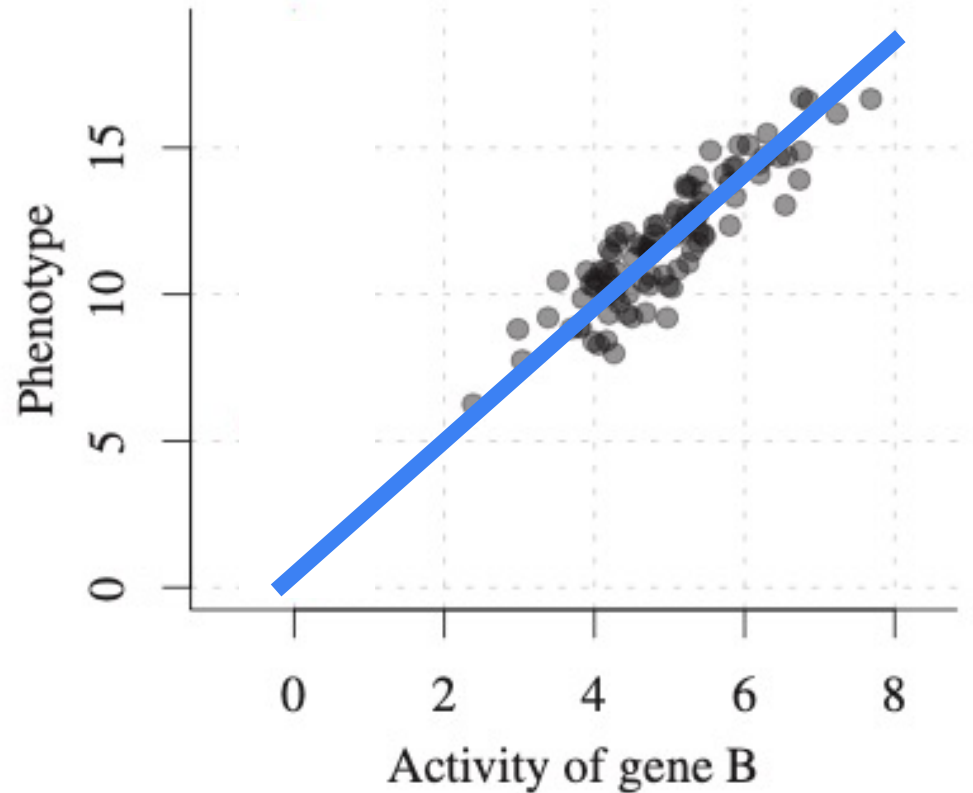
Again, my
question to you:

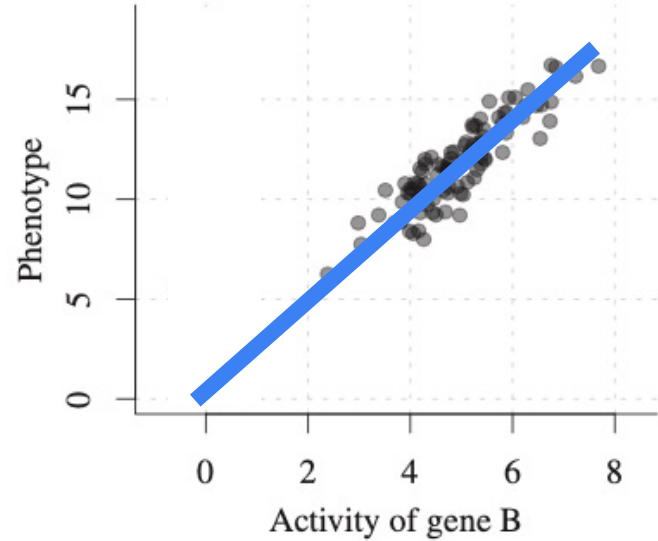
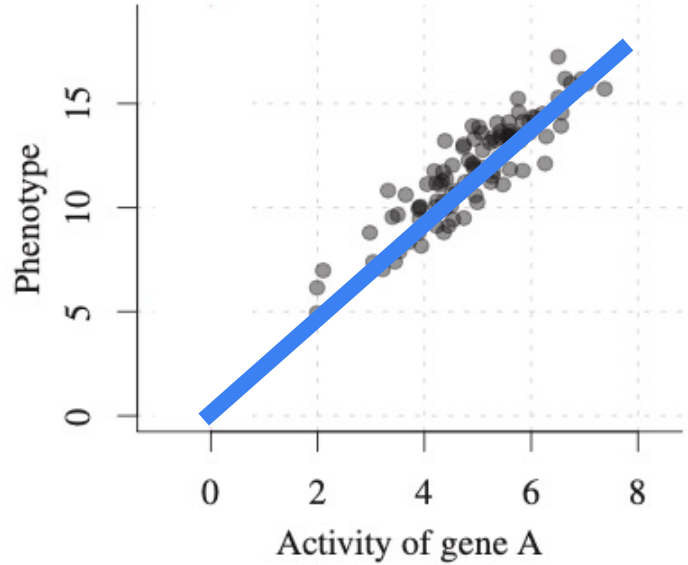
“How would
you do it?”



Learn a **Model**

Model learns a
linear function





...

Pharma loves you.
You give them all the answers they want!

Pharma will deploy now!

They have a **1B \$ experiment** inline.

Based on **your predictions**,
they can cut off phenotype expression by suppressing the genes.

Many plagued american lifes will be changed for the better now
that their sympoms will finely vanish after this procedure...

Experiments on Gene A were successful!

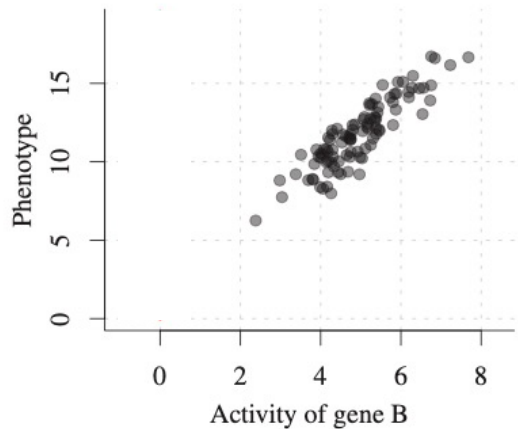
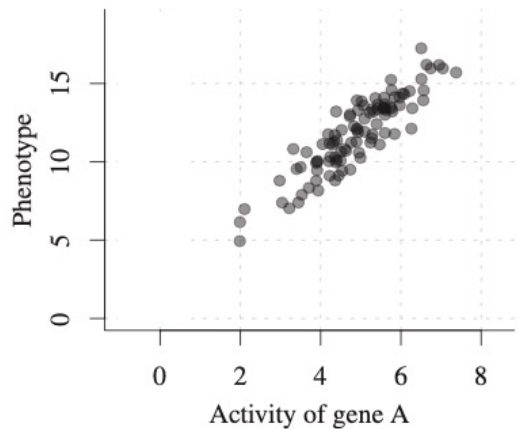
You saved many lives
by providing predictions that turned out to be true!

Experiments on Gene B were a total disaster!

Shit... what do we do now? Who is responsible?

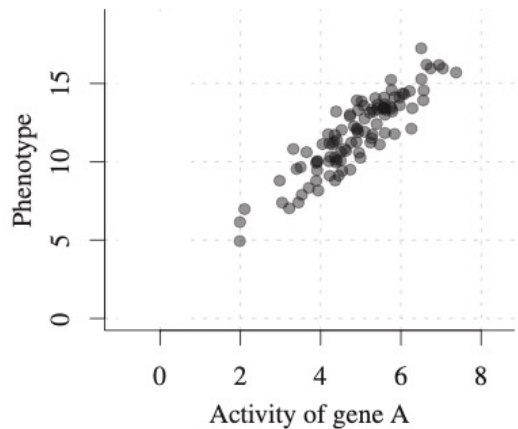
Well, you did this, you devil!

Let's go back in time,
shall we?

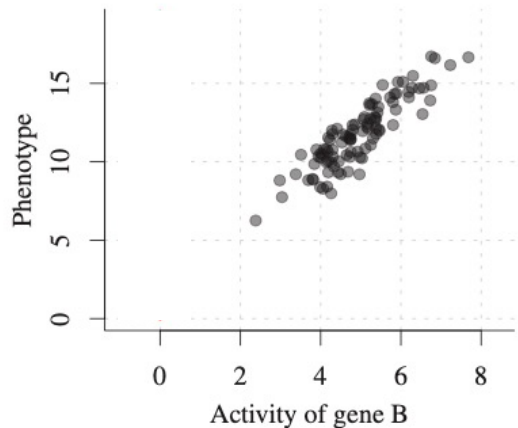


In ML for
instance, we'll
encounter data
sets like on the
left...

Dataset I

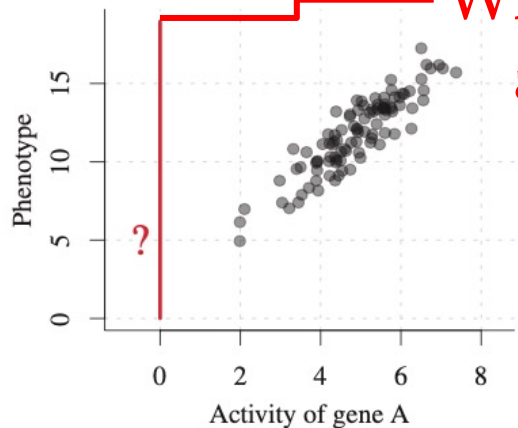


Dataset II



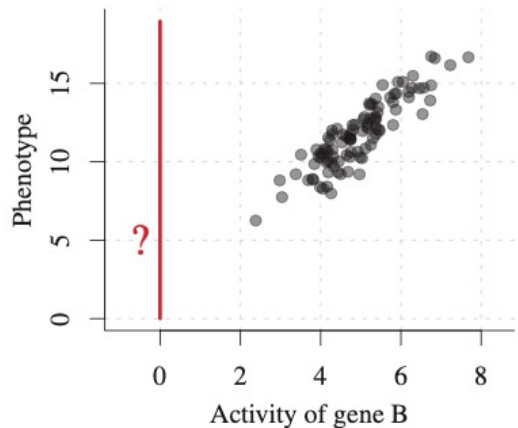
But, what is the
difference
between
datasets I & II
w.r.t. learning?

Dataset I



What if we kill the
activity of the
gene?

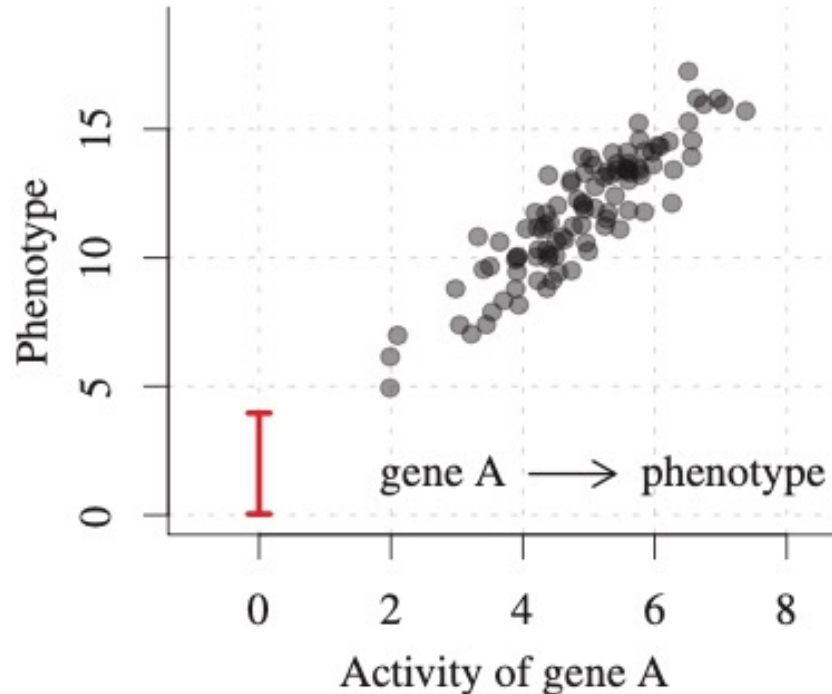
Dataset II



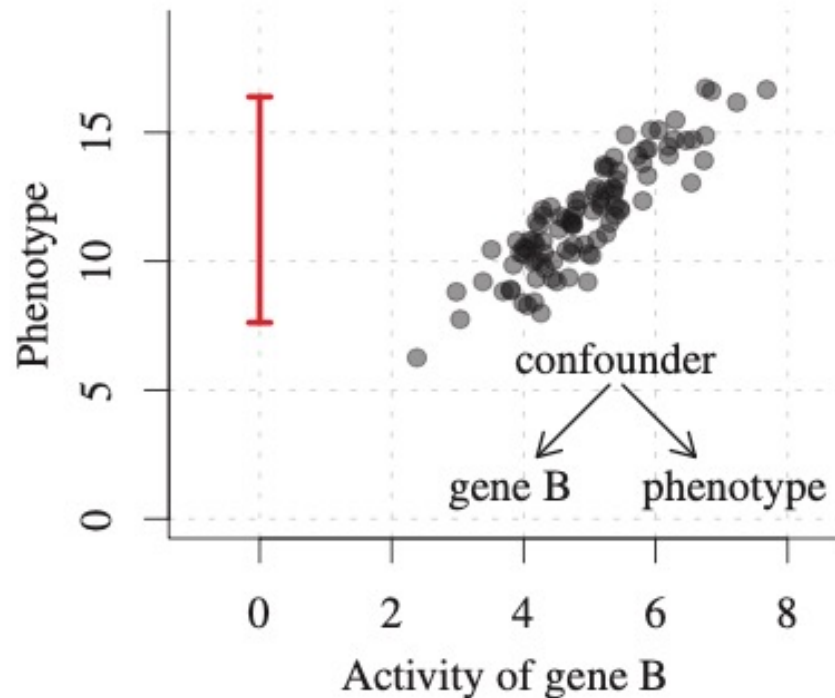
We might
ask about the
difference w.r.t.
generalization!

That is, looking *outside*
the original sample!

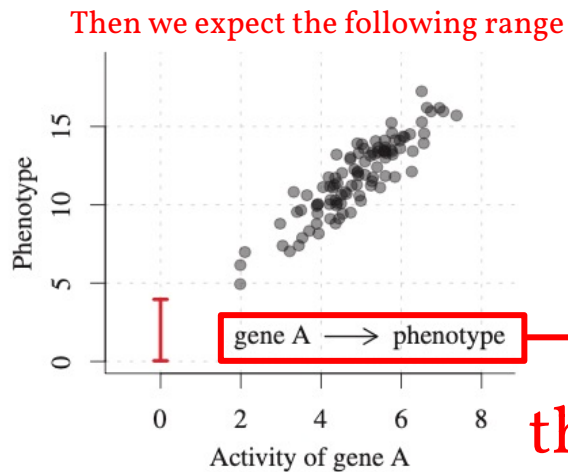
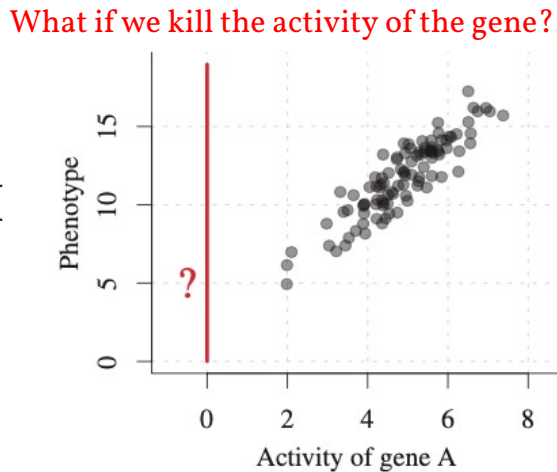
Changing gene *A* *will change* the phenotype,
that is **why** our 1st experiment worked!



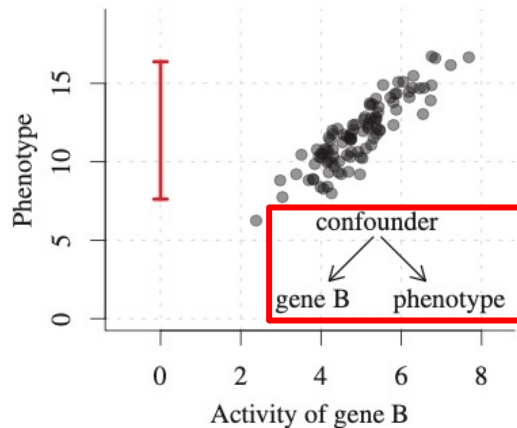
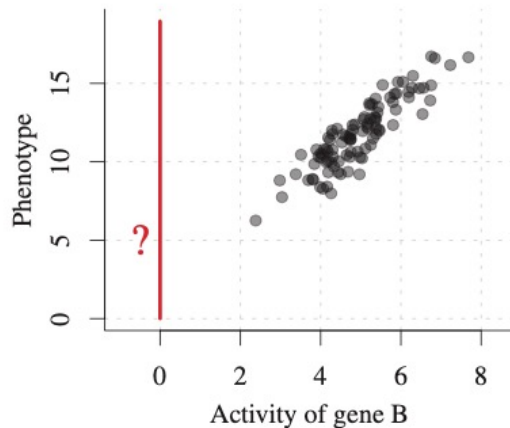
Changing gene B *will not change* the phenotype,
that is **why** our 2nd experiment failed!



Dataset I



Dataset II



the difference is
in the underlying
Causality!

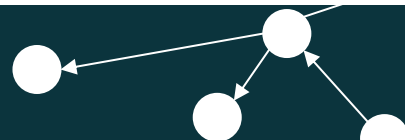
If you had considered
causality, then those
lives could've been saved
maybe...

Causal Inference

modelling assumptions **outside** the data
identification & estimation
graph learning
etc.

Reichenbach's principle Identification Simpson's Paradox CHT
Disentanglement
Interventions DAGs dHSIC Pearl's Hierarchy ATE
Confounder Counterfactuals Causal Effects CXPlain
d-separation Counterfactual Fairness Granger causality
NCM Ignorability Potential Outcomes Fundamental Problem of CI

Causality is Alive!



Causal Representation Learning
Structural Causal Model
Bayesian Network
Counterfactual Distance RCT RFVs GES "Clever Hans" Fallacies
DCD-FG Actual causality but-for
Causal Discovery Causal Parrots
ANMs Adjustment Set Faithfulness
do-calculus FCI Markovianity
Weak Sufficiency Exogenous PC interventional SPNs

Next up: **Code Tutorial**

Go to

continualcausality.org/program/

to access the code