Structural Equation Modeling

Day 3, Session 3

Specification

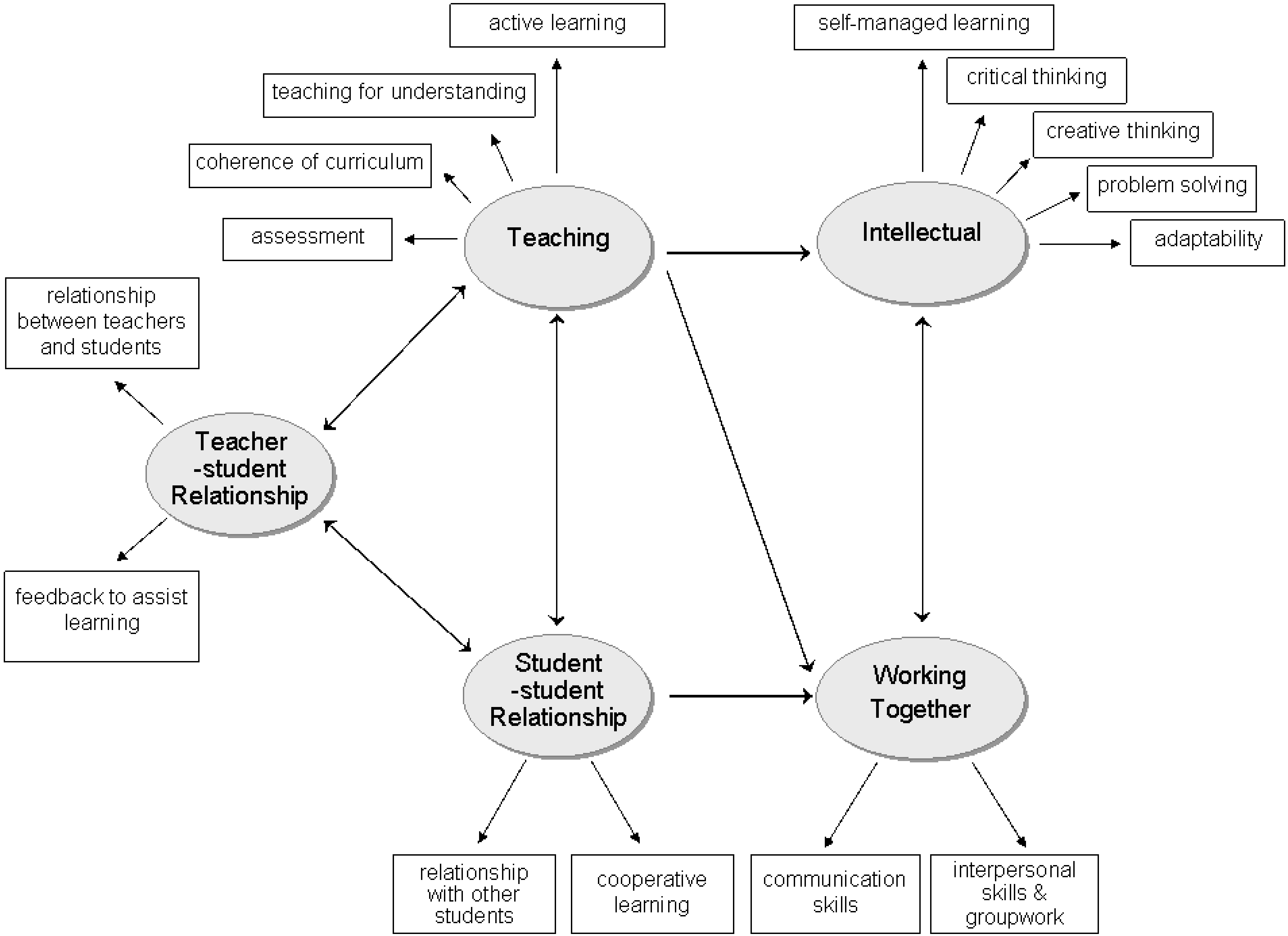
- Specification means the way we've built/constructed/specified our model
  - The terms we are estimating
- Structural model specification
  - Classic regression relationships among (latent) variables of substantive interest
- Measurement model specification
  - Relationships among observed and latent variables, including variances and covariance
- Specification = hypothesized model of the world

It's All Just Regression

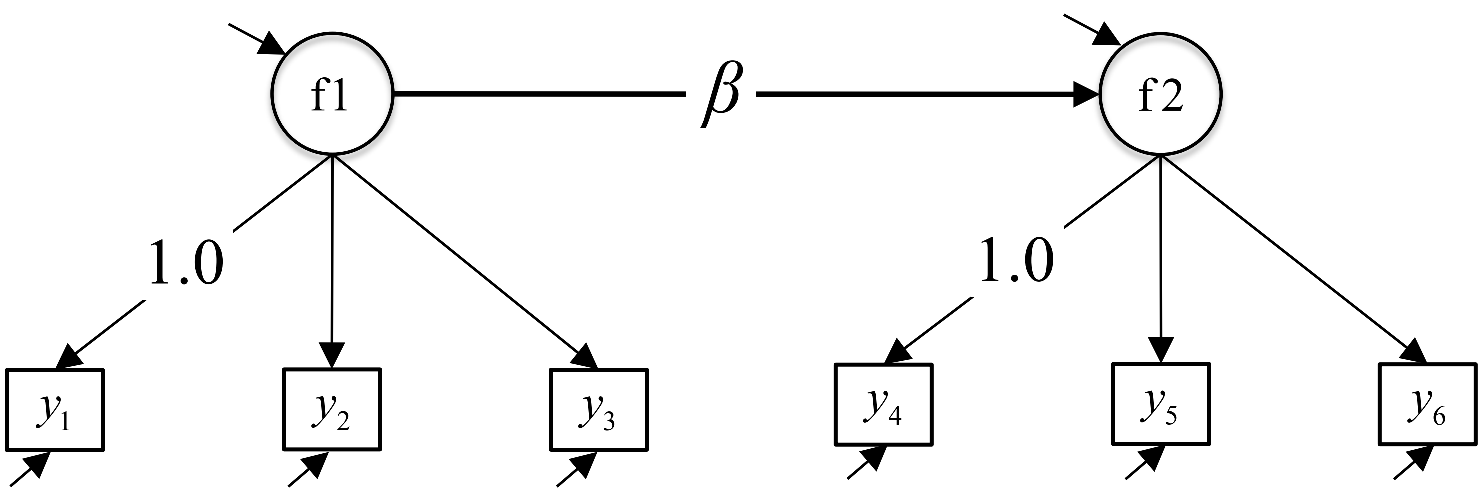
- We know structural models via path analysis
- We know measurement models via CFA
- Let's combine them[1,2]

- SEM = measurement model + structural model
  - Specify # of factors and factor loadings with "**BY**"
  - Specify regression/covariance with "**ON**" and "**WITH**"

- So, SEM solves two regression problems:
  - Simple structural models
  - Variables measured with error


active learning
teaching for understanding
coherence of curriculum
assessment
Teaching
self-managed learning
critical thinking
creative thinking
problem solving
adaptability
Intellectual
relationship between teachers and students
Teacher -student Relationship
feedback to assist learning
Student -student Relationship
Working Together
relationship with other students
cooperative learning
communication skills
interpersonal skills & groupwork

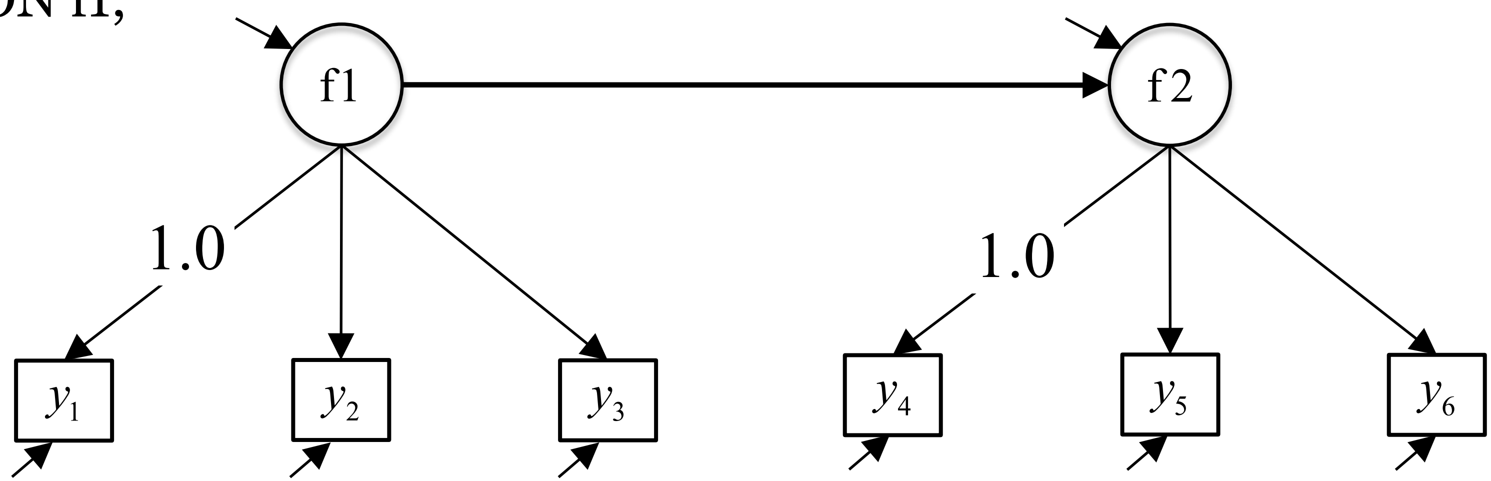
Might Start With…



Seems Simple...

- Seems straightforward
  - We know how to do path analysis and CFA
  - Just add more variables and specify your models
- Model:

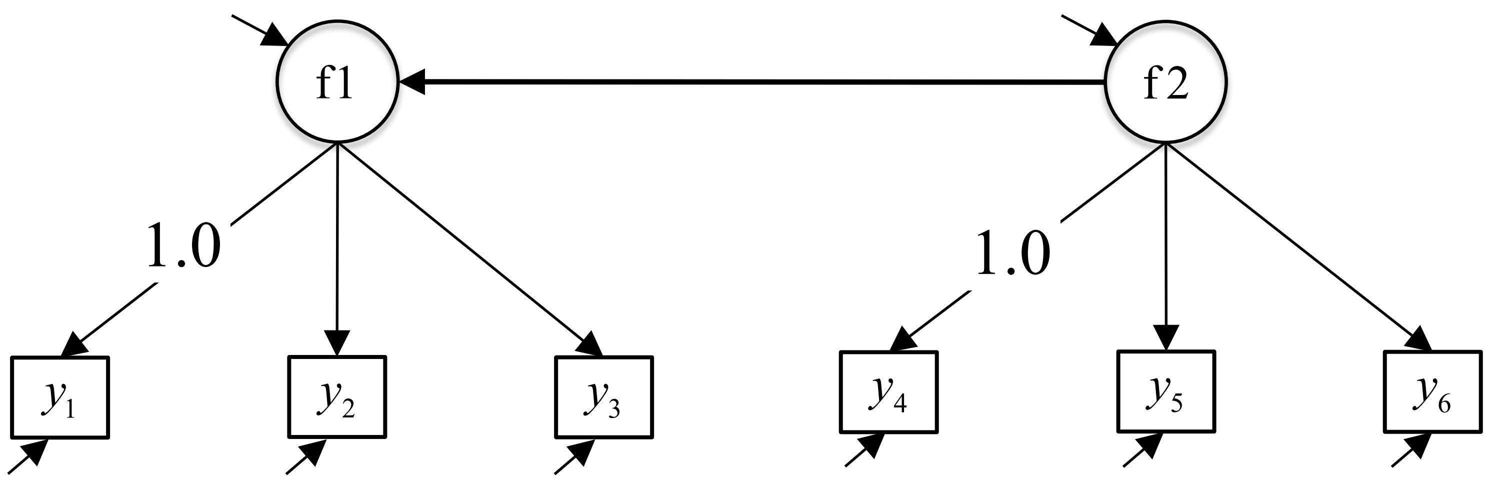
```
f1 BY y1-y3;
f2 BY y4-y6;
f2 ON f1;
```



And This?

- Model:

  f1 BY y1-y3;
  f2 BY y4-y6;
  ???



Estimation and Fit

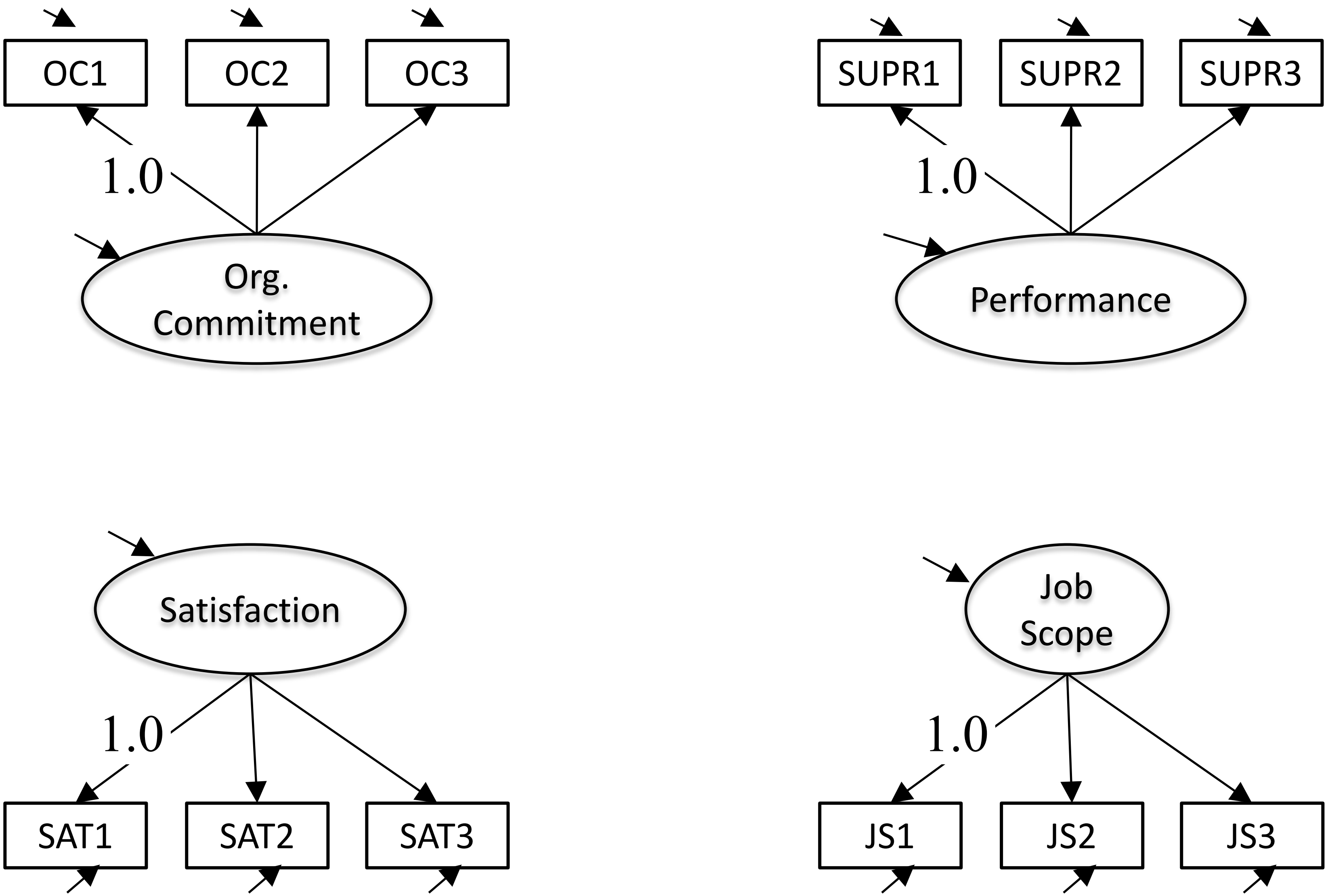
- Just as before for ML:
- We estimate until our model best fits the data
- We compute fit based on the difference between our estimated model and what we've observed
  - We'll cover fit soon
- Reporting standards vary across fields[3]

- Just as before for Bayesian estimation:
- We estimate until we achieve stable estimates
- We check our model with *PPP*-values

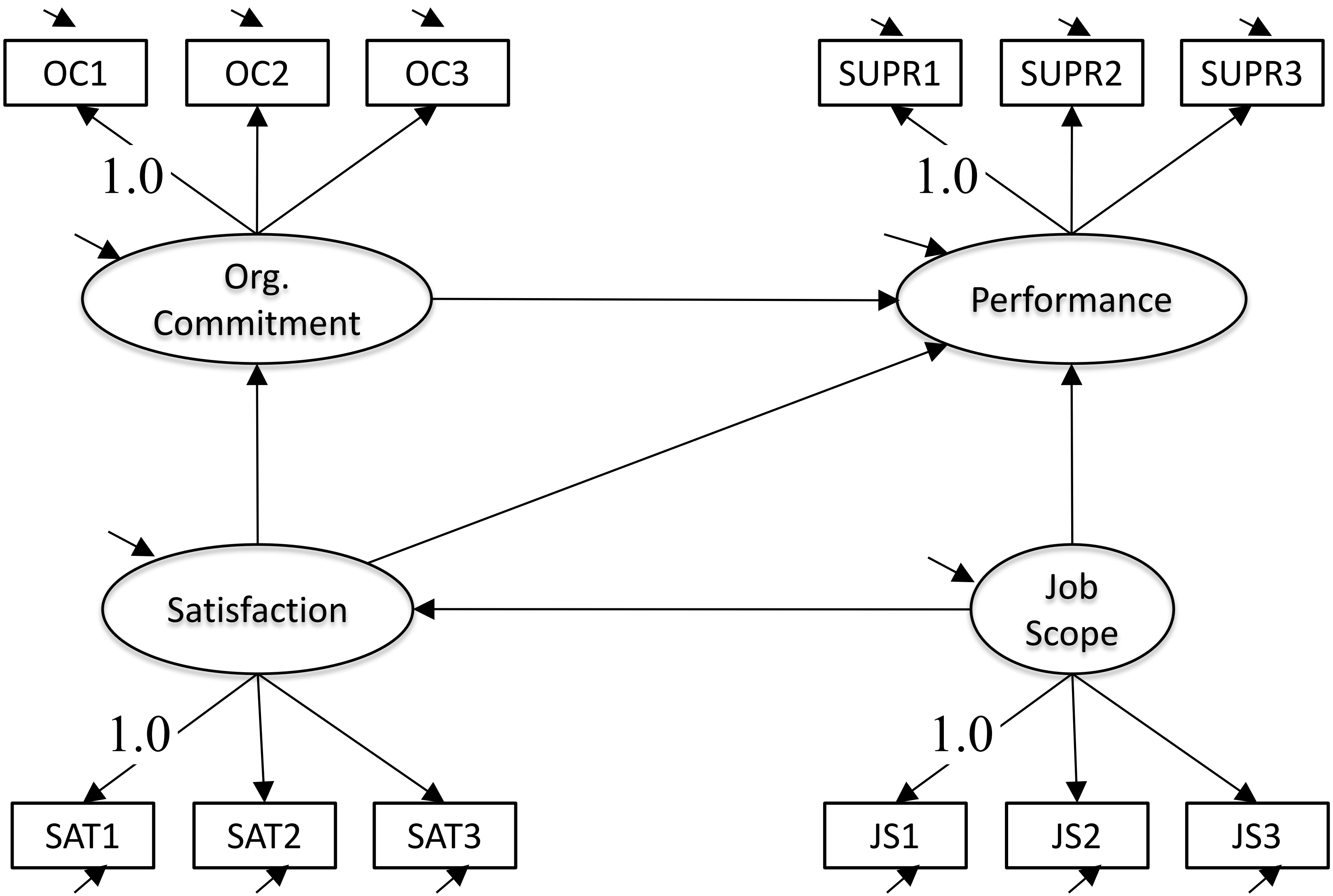
Specification

- Just as before:
- We need to scale our latent variables
  - Factor loading or variance set to 1.0
- We can specify covariance or regression among latent variables
- Covariation among observed variables possible
  - Regression as well, but not important here
- Our specification is a model of the world!
  - Choose specification based on theory

Causal Effects Here?



Example (SEM1.inp)



SEM1.inp

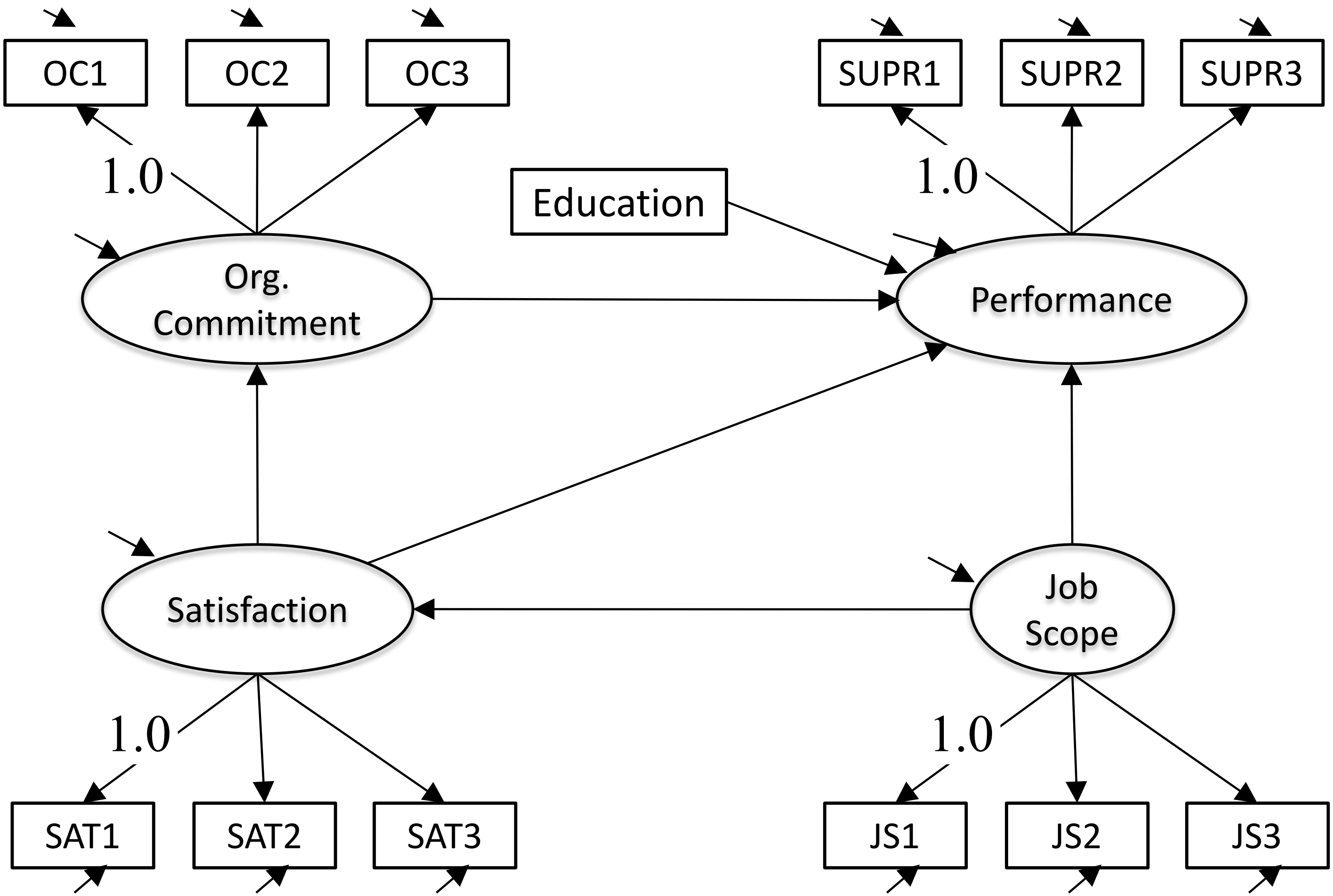
- Model:

```
OC by OC1 OC2 OC3;
SAT by SAT1 SAT2 SAT3;
JS by JS1 JS2 JS3;
PERF by SUPR1 SUPR2 SUPR3;

PERF on OC SAT JS;
OC on Sat;
Sat on JS;

! If you have a different theory, change the structural model
! Let's go back to beginning and rethink their theory
! Keep in mind the endogeneity problem… what about causality??
```

What about Controls?

- We can include any additional variables we'd like
- Which variables might affect performance
  - Education, Position Tenure, Org Tenure, or Age?

Example (SEM2.inp)



SEM2.inp

- Model:

```
OC by OC1 OC2 OC3;
SAT by SAT1 SAT2 SAT3;
JS by JS1 JS2 JS3;
PERF by SUPR1 SUPR2 SUPR3;

PERF on OC SAT JS Education;
OC on Sat;
Sat on JS;
```

Indirect Effects?

- We have indirect effects embedded in the model
- We can again use MODEL INDIRECT:
  - IND command
- We should bootstrap confidence intervals
  - In this case, we don't have individual data, so can't

SEM3.inp

- Model:

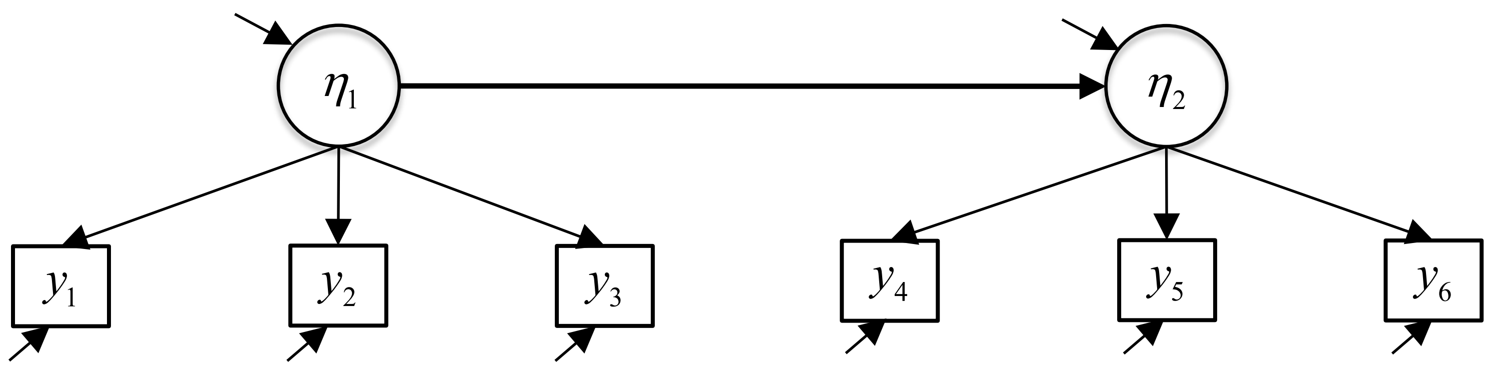
```
OC by OC1 OC2 OC3;
SAT by SAT1 SAT2 SAT3;
JS by JS1 JS2 JS3;
PERF by SUPR1 SUPR2 SUPR3;

PERF on OC SAT JS Education;
OC on Sat;
Sat on JS;
```

- Model Indirect:

```
Perf IND JS;
```

Steps in Model Building

- Misfit of theoretical model are **very** common
- Huge debate over how to proceed for deductive sci.
- We have possibility of:
  - Exploration of measurement with EFA
  - Confirmation of measurement with CFA
  - Structural specification in SEM
- For frequentists, very easy to capitalize on chance



Practical Steps: 2 Step

- 2-step[4]
  - CFA with "fully-saturated" covariance structure
    - Allow all LVs to freely covary (i.e., only WITH, no ON)
    - Removes structural model from estimation of fit
    - Misfit can only be due to measurement model problems
  - Obtain fit to evaluate measurement model
  - Estimate structural model with regression
  - Obtain fit & contrast with previous model
    - Changes in fit due to structural model misfit

- Bayesian estimation?
  - Can compare *DIC*, but there's little guidance here

Practical Steps: 4 Step

- 4-step[5,6]
  - Exploratory search for # of factors
  - CFA with fully-saturated covariance structure
  - Estimate structural model with regression
  - Test nested/alternative models
    - Let's first talk about model identification and model fit …

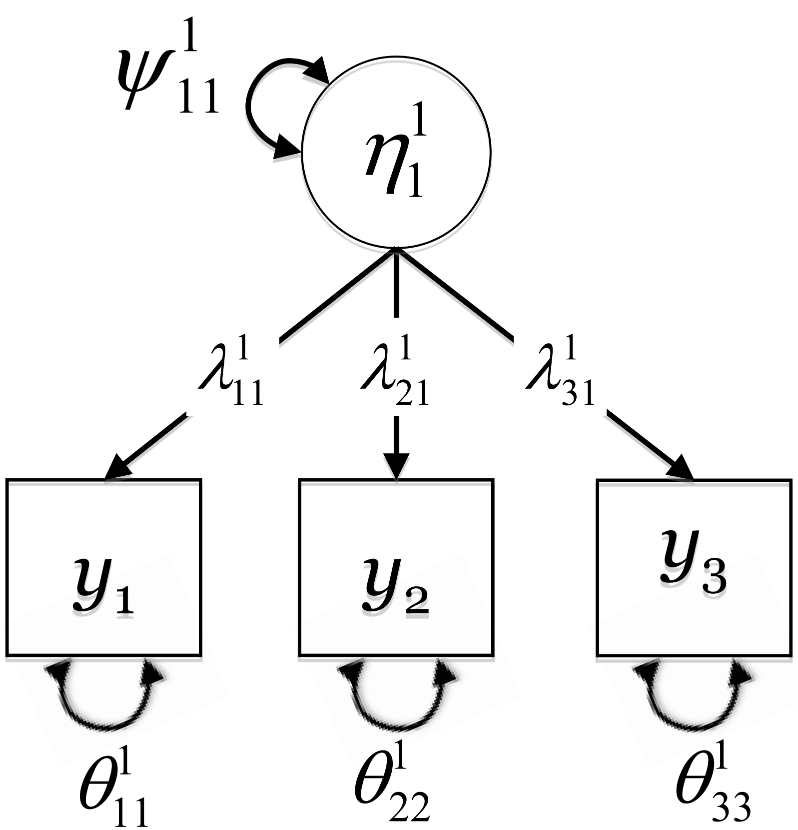
- Relates to ability to make causal inferences
  - (Kind of a big deal in science)
  - How is the debate quietly framed by frequentism?
- For generally commentary see[7]

Multigroup Contexts[8]

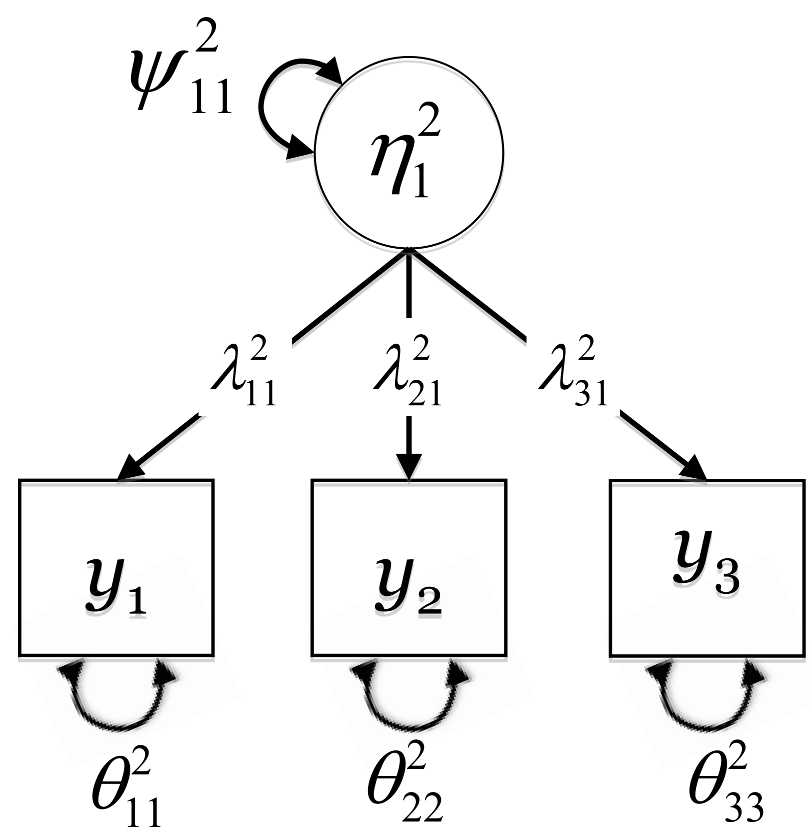
- Cross-cultural research
  - Look at similarity in nomological nets/structural parameters
- Selection/Employment contexts
  - Look for DIF or other forms of bias in measurement parameters
- Would be convenient if we could estimate parameters from multiple groups ☺

Might Show It As

Group 1



Group 2



Estimation & Specification

- Both groups must have same observed variables
- Must be nested
- Best fitting parameters derived for each group separately
- Likelihood derived for each group
- Combine for total model likelihood
- Overall measures of model fit for both groups

Mplus Logic

- Have an overall model specification both groups

- Then have group-specific specifications
  - I.e., group-specific Model: commands
  - These must be nested in the overall specification
  - Anything you refer to in a group-specific specification becomes freely estimated

Meaning of Differences?

- Variance in parameters across groups is like a group*predictor interaction
- Conceptually, it's moderation by group
- Instead of including dichotomous dummies, can estimate a multi-group model
- Much easier to estimate multi-group models
  - Consider group by LV interactions…

Multi-Group Invariance Testing[8,9]

- To test equivalence in structural parameters we require invariance in measurement parameters[9]
- Lots of literature here[8]

- It's a snap to test
  - Step 1: Estimate unconstrained model
    - Parameters freely vary across groups
    - Observe χ^2, *df*, and fit indices
  - Step 2: Constrain parameters to equality
    - Take difference in χ^2 and *df* for significance testing
    - Compare other fit indices[10,11]

Summary

- SEM is simply path analysis + CFA
  - Model-based procedure
  - Model comparisons allow testing theory
  - It's easy to setup, but with complicated models…
- Multigroup models
  - Convenient for simultaneous analysis
  - Allows invariance testing
  - Lots to read here (see introductions)[12,13,14,15]
    - E.g., steps in conducting analyses of invariance, etc.

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