THE WATCHME STUDENT MODEL EXPLAINED

(MAASTRICHT, OKTOBER 6)

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THE WATCHME STUDENT MODEL

- **Student Model = A representation of the variables and their relations that play a role in a (workplace-based) learner (e.g., performance level, motivation, consistency).**

- **We use a Bayesian network for this representation. It is grounded in classical probability theory and allows us to predict the inner state of a student on the basis of observed evidence.**

- **The type of Bayesian network we apply is called Multi-Entity Bayesian Network, which makes it possible to take the student's particular context into account, and allows a more clear way of defining the model.**

THE WATCHME STUDENT MODEL

- **As input, our model uses e-portfolio content (e.g., assessments, scores), or findings generated from the content (e.g. a sudden drop in scores)**

- **The output are posterior probability tables for the variables, given the observed. (e.g., p(motivation=high)=0.7, p(motivation=low)=0.3)**

- **This output is used for presenting appropriate messages to students or their supervisors. (e.g., if p(motivation=low) > 0.5 display: “Please contact your mentor to talk about your study progress”)**

THE WATCHME STUDENT MODEL

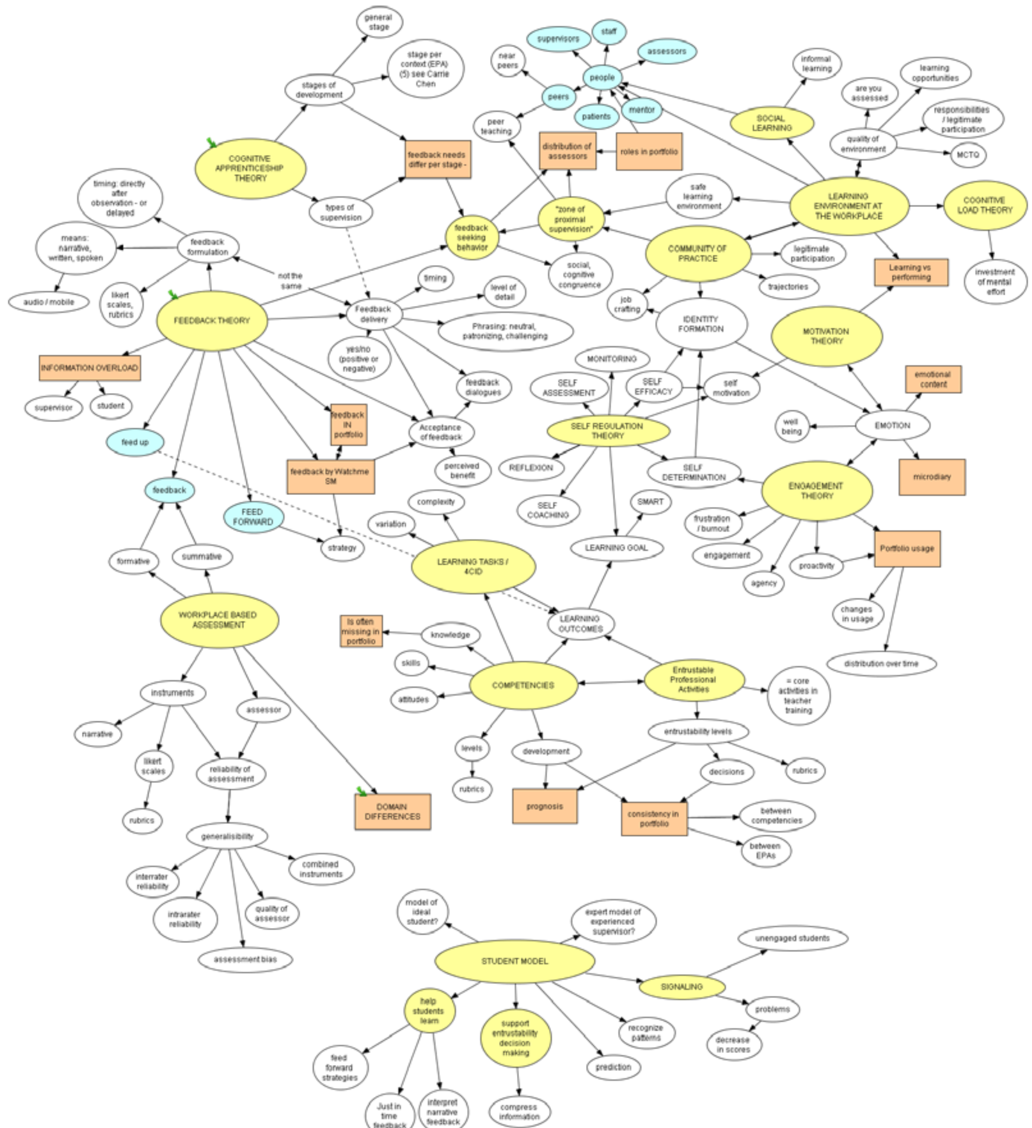
- In WATCHME we produced two different student models that are used in parallel:

- The PERFORMANCE MODEL takes the assessment scores directly from the portfolio and tries to estimate the true present level of performance. It does this per EPA and per performance indicator in the EPAs. It also takes a few narrative feedback fields into account, that are translated in a sentiment level.

- The PEDAGOGICAL MODEL concentrates more on the behavioural and meta-cognitive aspects. In this presentation, we will concentrate on this second model.

DESIGNING THE MODEL

- Before building the pedagogical model, we needed to decide on what variables to include in the model.
- We interviewed 12 scholars involved in workplace-based learning on what educational theories and concepts that are linked to this area.
- From the interviews, a mind-map was created that interlinks all terms and theories mentioned in the interviews



Mind map of concepts in workplace-based learning

DESIGNING THE MODEL

- **From this mind-map, we selected 5 themes, which we judged to be feasible to implement into the student model on the basis of e-portfolio content.**
- **The five selected themes are:**
  - Feedback seeking behaviour
  - “Frustration alert”
  - Completeness of information
  - Portfolio consistency
  - Need for feedback (currently not implemented)
- **We discussed the themes with representatives from each of the three WATCHME application domains for further details and refinement**

BUILDING THE MODEL

- **In a Multi-Entity Bayesian Network, each of the themes is represented by what is called a “knowledge fragment”. Such a fragment contains the variables that are important in that theme and defines the probabilistic relations between them.**
- **Each knowledge fragment contains** input variables **that either are fed with evidence from the portfolio, or that can come from other knowledge fragments**
- **Each knowledge fragment contains** output variables
- Intermediate variables **can be used to define more complicated relations between input and output.**
- **A fragment also has** parameters **that dictate when and how and how often the fragment is applied**
- **The tool UnBBayes was used to build and run the model**

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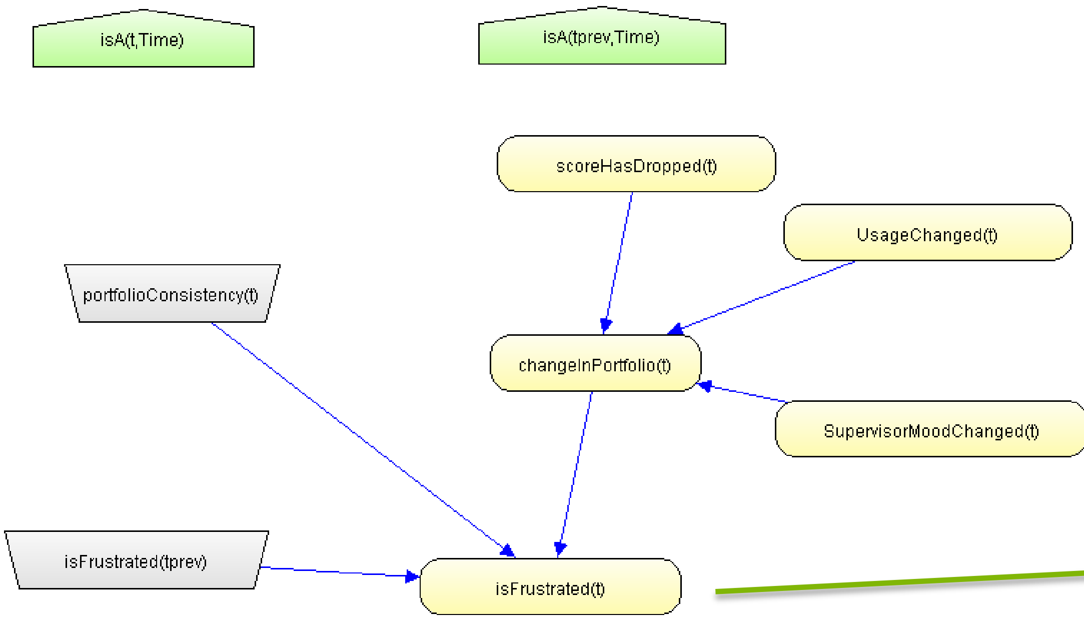
BUILDING THE MODEL



The knowledge fragment for “Frustration alert”

Each variable has a probability function connected to it:

```
if any t have ( portfolioConsistency=InconsistencyHigh &
changeInPortfolio=significantChange) [

  if any tprev have ( isFrustrated = FrustrationHigh) [  FrustrationHigh = 0.95,
FrustrationLow = 0.05 ]
  else [  FrustrationHigh = 0.8,   FrustrationLow = 0.2 ]

] else [ if any t have ( portfolioConsistency=InconsistencyHigh &
changeInPortfolio=mildChange) [

  if any tprev have ( isFrustrated = FrustrationHigh) [  FrustrationHigh = 0.7,
FrustrationLow = 0.3 ]
  else [  FrustrationHigh = 0.6,   FrustrationLow = 0.4 ]

] else [ if any t have ( portfolioConsistency=InconsistencyHigh &
changeInPortfolio=noChange) [

  if any tprev have ( isFrustrated = FrustrationHigh) [  FrustrationHigh = 0.2,
```

PROBABILITY TABLES

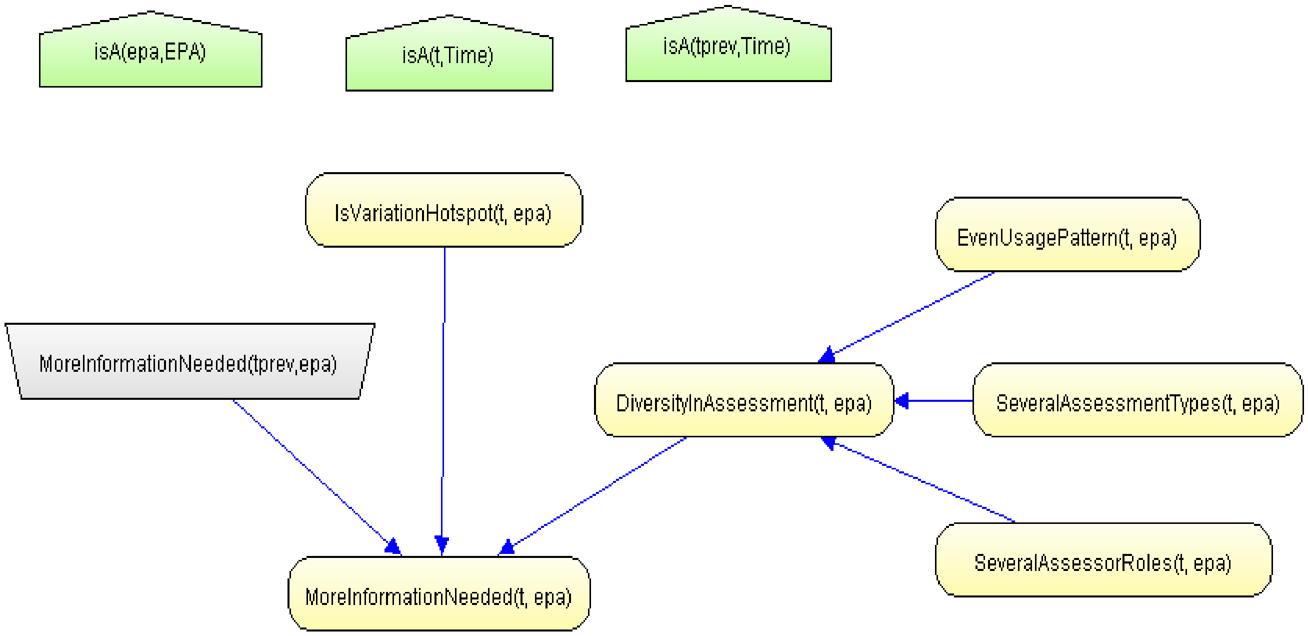
Node: change in portfolio

Condition	Signif. change	Mild change	No change
Strong drop in score	0.90	0.09	0.01
Little drop & usage change & sup. mood change	0.80	0.15	0.05
Little drop | usage change | sup. mood change	0.10	0.80	0.10
Else	0.05	0.15	0.8

Node: is Frustrated?

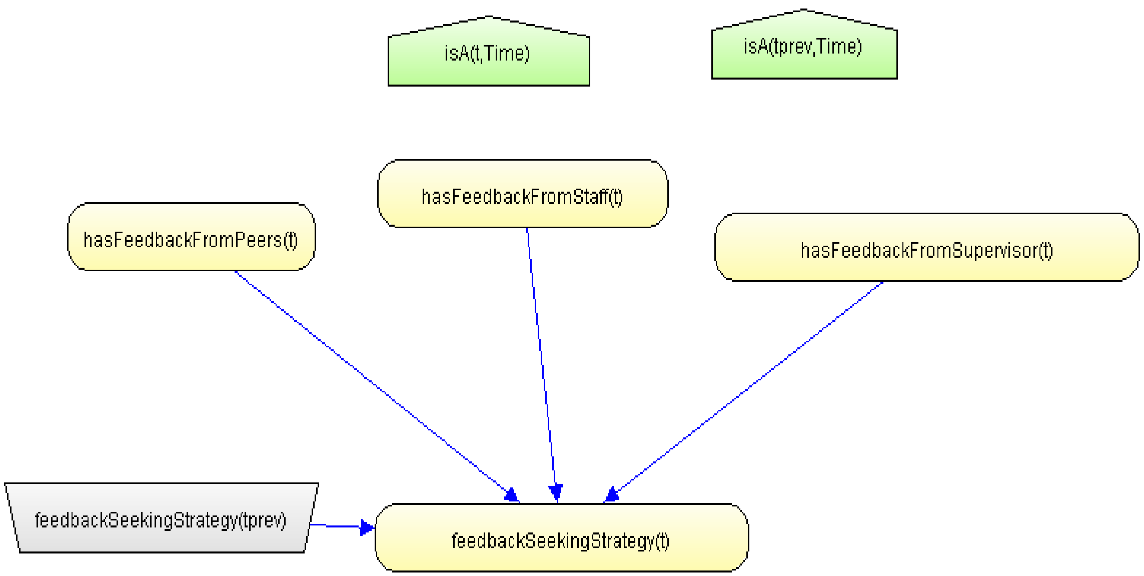
	(low on previous time)		(high on previous time)	
Condition	Low	High	Low	High
High inconsist. & signif. Change	0.20	0.80	0.05	0.95
High inconsist. & no or mild change	0.30	0.70	0.20	0.80
Medium inconsist & Signif. Change	0.40	0.60	0.30	0.70
Low inconsist & mild or signif change	0.80	0.20	0.50	0.50
else	0.95	0.05	0.95	0.05

BUILDING THE MODEL



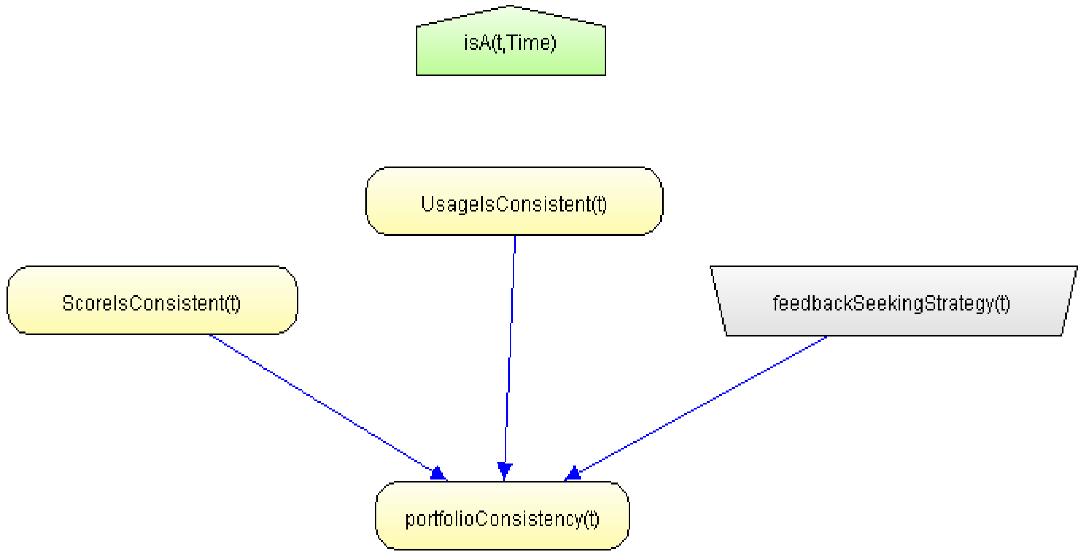
The knowledge fragment for “Completeness of information”

BUILDING THE MODEL



The knowledge fragment for “Feedback Seeking Behaviour”

BUILDING THE MODEL



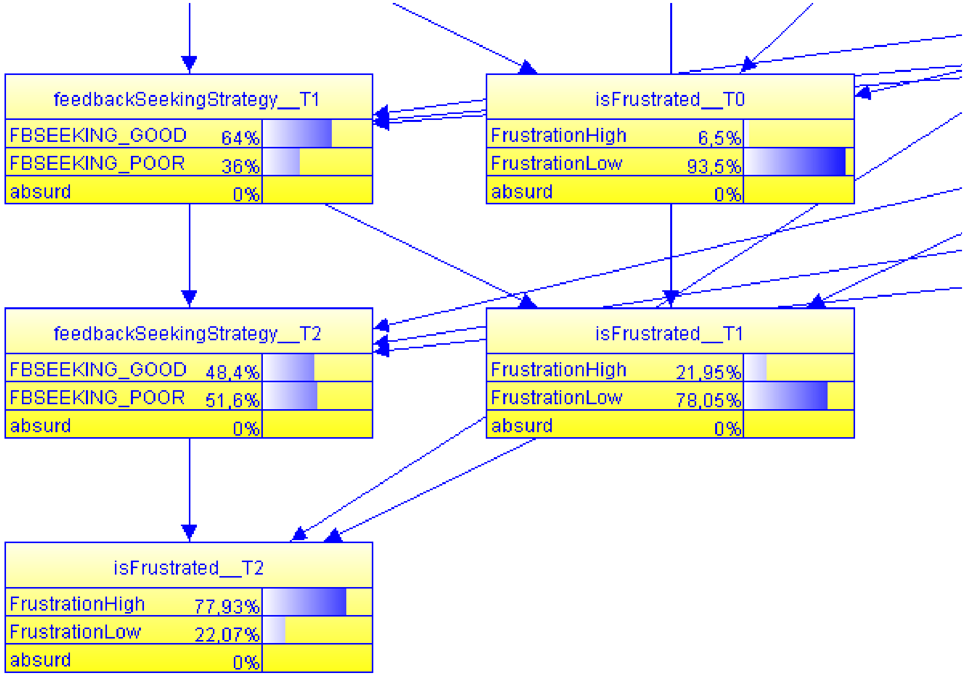
The knowledge fragment for “Portfolio Consistency”

RUNNING THE MODEL

After adding evidence to the model, the model can be queried, e.g.

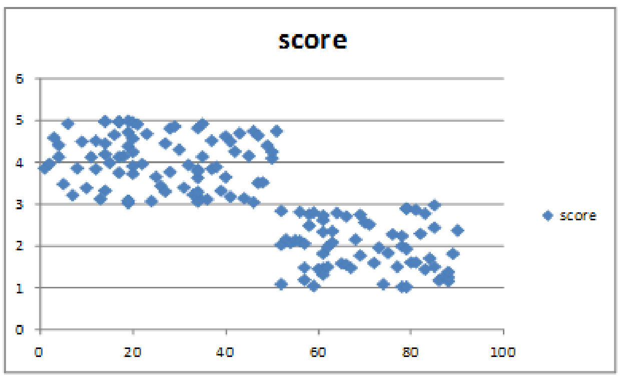
“what is the level of frustration at time T2?”

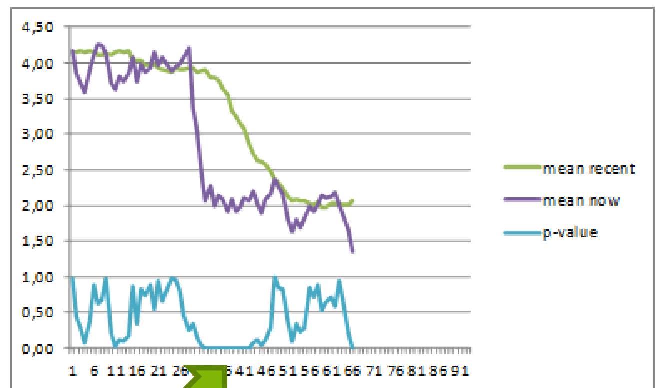
A Bayesian network will then be created that answers the query:



GETTING THE EVIDENCE

- To fill variables like “scoreHasDropped(t)” we need to extract this information from the e-portfolio
- We created a series of statistical functions that take the assessments from the portfolio (with the time points of the assessment) and determine for each of the time if, for instance, a drop in score can be detected





T-statistic

FINDING-GENERATING FUNCTIONS

These functions are:

- **ScoreDropped (two time windows of scores, t-test)**
- **UsageChanged (two time windows, avg. usage, t-test)**
- **MostVariation (one time window, scores per EPA, F-statistic)**
- **usageConsistency (one time window, avg. usage, ANOVA)**
- **scoreConsistency (one time window, scores, ANOVA)**

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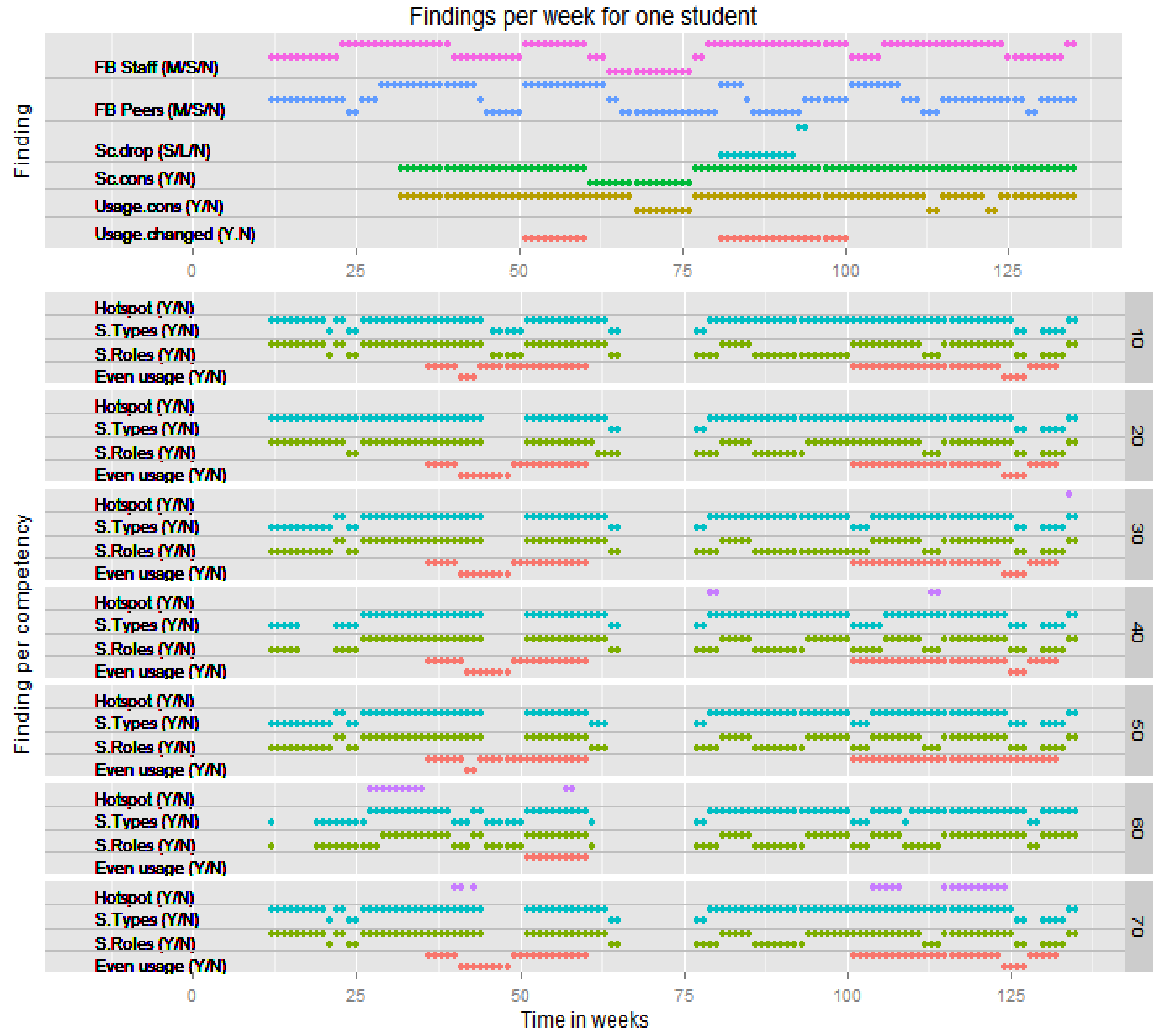
TUNING THE MODEL

- The model and the finding-generating functions contain many parameters that need to be tuned.
- Some parameters can be deduced from literature, but most of them need to be fine-tuned to the application domain.
- We took a set of anonymized historical portfolio data to tune the WATCHME model. It did not include EPAs, so competencies were used instead.
- First, the parameters for the finding-generating functions were tuned so that not too many but also not too little findings where detected.
- Then we ran the student model for all portfolio’s in the set for all points in time and inspected the model output.
- This resulted in some changes in probability functions.

Findings generated for a fictive student



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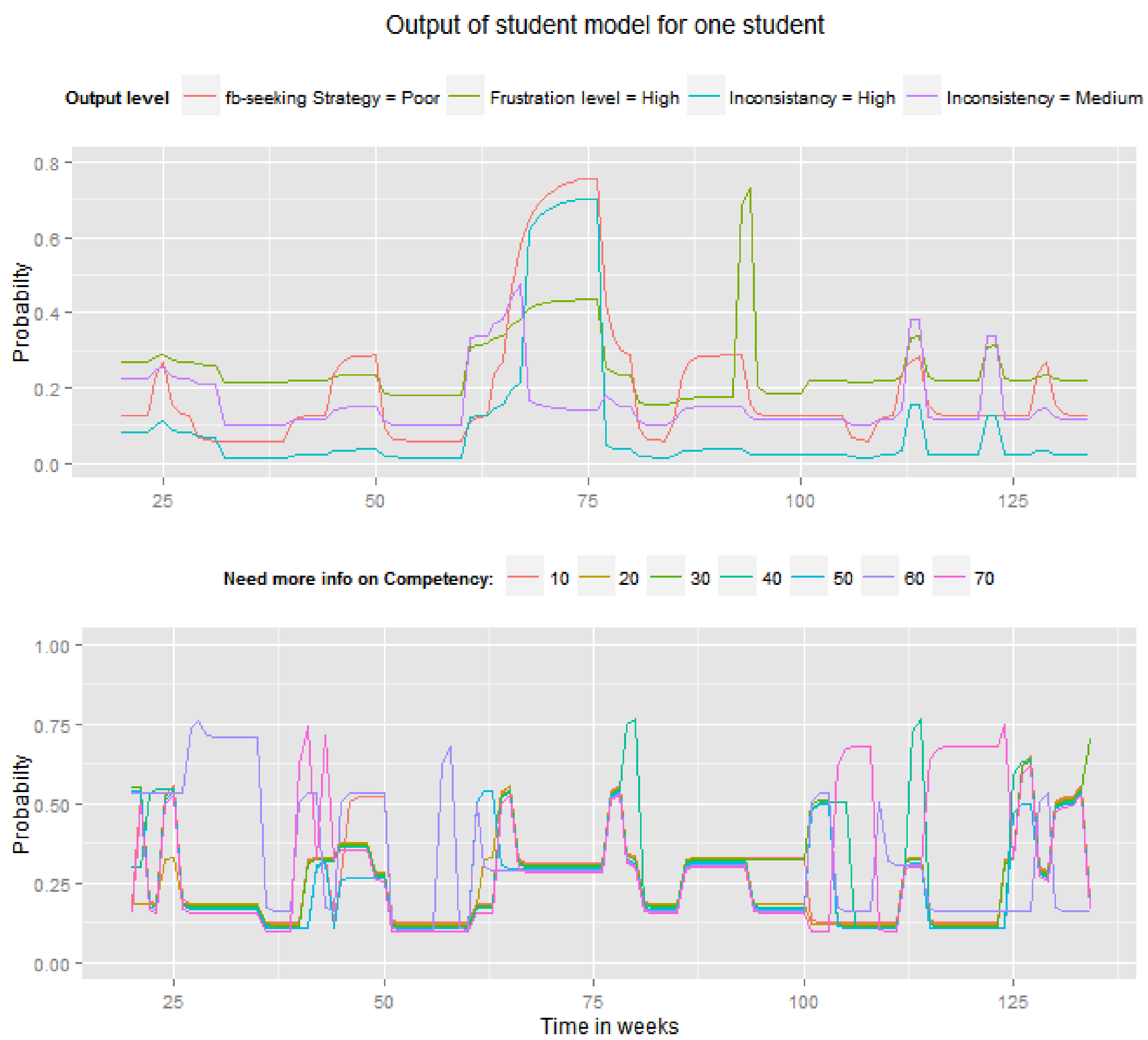


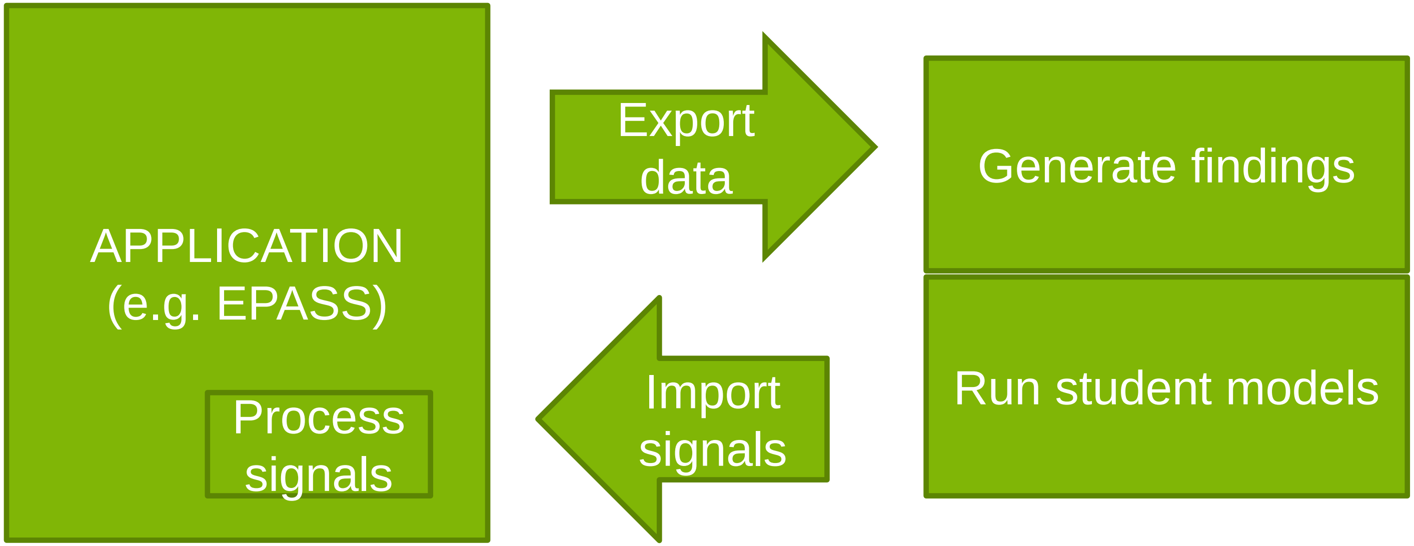
Model output for a fictive student

THE PROOF OF THE PUDDING…

- **Tuning the model and the parameters on the basis of historical data is necessary, but only the starting point**
- **The field-experiments in WATCHME are started**
- **Retuning of parameters might be needed along the ride**

- **Research questions:**
  - Exact phrasing and timing of feedback-messages is important and context dependent. What is the best for this situation? What other communication is possible, e.g. what visualisations could be used?
  - Will students change their behaviour on the basis of output generated by the model?
  - What other elements can be included in the model?
  - In what contexts and circumstances does such a model work best?

FUTURE DEVELOPMENTS



CONCLUSIONS

- **We were able to show that it is possible to build and run a pedagogical student model for workplace based learning using e-portfolio data**

- **The MEBN technology is very useful for constructing student models**
  - Modularity and flexibility
  - Direct translation of concepts from educational theory into knowledge fragments
  - Heuristics (rules of thumb), experimental evidence, data collected in practice can be incorporated

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CONCLUSIONS

- **Translation of raw data into meaningful findings is always needed**

- **Careful instructional design is needed to deal with the student model output**
  - How,
  - When,
  - To whom to deliver?

- **Many opportunities for educational research!**

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