



Seminar *Trends in Computer-Aided Verification*

Introduction

Summer Semester 2021; April 14, 2021

Thomas Noll et al.

Software Modeling and Verification Group

RWTH Aachen University

<https://moves.rwth-aachen.de/teaching/ws-20-21/propro/>

Outline

Overview

Aims of this Seminar

Important Dates

Verification of Neural Networks [Christopher Brix, Thomas Noll]

Analysis of Bayesian Networks [Bahare Salmani]

Synthesizing Quantitative Loop Invariants for Probabilistic Programs [Mingshuai Chen]

Formal Approaches to Systems Engineering [Shahid Khan]

Final Hints

Formal verification methods

- Rigorous, mathematically based techniques for the specification, development and verification of software and hardware systems
- Aim at improving correctness, reliability and robustness of such systems

Formal verification methods

- **Rigorous, mathematically based techniques** for the specification, development and verification of software and hardware systems
- Aim at improving **correctness, reliability and robustness** of such systems

Classifications

- According to **design phase**
 - specification, implementation, testing, ...
- According to **specification formalism**
 - source code, neural networks, Bayesian networks, fault trees, ...
- According to underlying **mathematical theories**
 - model checking, theorem proving, static analysis, ...

Areas Covered in this Seminar

Topic areas

- Robustness Analysis of Neural Networks
- Analysis of Bayesian Networks
- Synthesizing Quantitative Loop Invariants for Probabilistic Programs
- Formal Approaches to Systems Engineering

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Goals

Aims of this seminar

- Independent understanding of a scientific topic
- Acquiring, reading and understanding scientific literature
 - given references sufficient in most cases
- Writing of your own report on this topic
 - far more than just a translation/rewording
 - usually an “extended subset” of original literature
 - “subset”: present core ideas and omit too specific details (e.g., related work or optimisations)
 - “extended”: more extensive explanations, examples, ...
 - discuss contents with supervisor!
- Oral presentation of your results
 - can be “proper subset” of report
 - generally: less (detailed) definitions/proofs and more examples

Requirements on Report

Your report

- Independent writing of a report of **12–15 pages**
- First milestone: **detailed outline**
 - not: “1. Introduction/2. Main part/3. Conclusions”
 - rather: overview of structure (section headers, main definitions/theorems) and initial part of main section (one page)
- **Complete** set of references to all consulted literature
- **Correct citation** of important literature
- **Plagiarism**: taking text blocks (from literature or web) without source indication causes immediate **exclusion from this seminar**
- Font size **12pt** with “standard” page layout
 - **L^AT_EX template** will be made available on seminar web page
- **Language**: German or English
- We expect the **correct usage** of spelling and grammar
 - ≥ 10 errors per page $\implies$ abortion of correction

Requirements on Talk

Your talk

- Talk of **30 minutes**
- Organised as Zoom meeting
- Focus your talk on the **audience**
- **Descriptive** slides:
 - $\leq$ 15 lines of text
 - use (base) colors in a useful manner
 - number your slides
- **Language:** German or English
- No spelling mistakes please!
- Finish **in time**. Overtime is bad
- Ask for **questions**
- Have **backup slides** ready for expected questions
- **L^AT_EX/beamer template** will be made available on seminar web page

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Deadlines

- April 18: Topic preferences due
- May 10: Detailed outline due
- June 7: Full report due
- June 28: Presentation slides due
- July 13 (?): Seminar talks

Important

Missing a deadline causes **immediate exclusion** from the seminar

Selecting Your Topic

Procedure

- Check out **Foodle poll** at <https://terminplaner.dfn.de/qhUSVZHyboDWZP63>
- Topics classified according to BSc/MSc level
- Please give at least three “Yes” votes ✓
- Preferably additional “Maybe” votes (✓)
- Give as **comment**:
 - preference of topics (if desired)
 - language of report and talk (English/German)
- **Fill form by Sunday, April 18**
- We do our best to find an adequate topic-student assignment
 - disclaimer: no guarantee for an optimal solution
- Assignment of topics and supervisors will be published on web site by mid next week

Withdrawal

- You have up to **three weeks** to refrain from participating in this seminar.
- Later cancellation (by you or by us) causes a **not passed** for this seminar and reduces your (three) possibilities by one.

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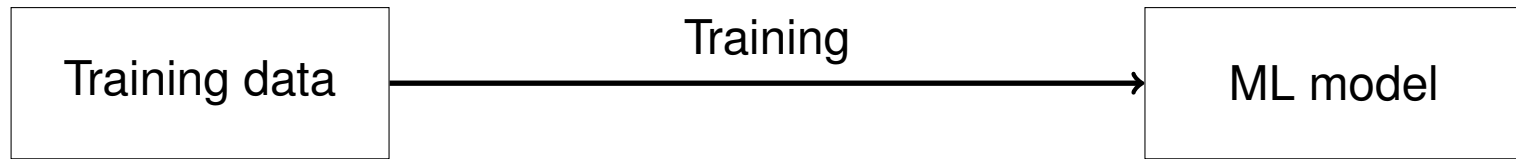
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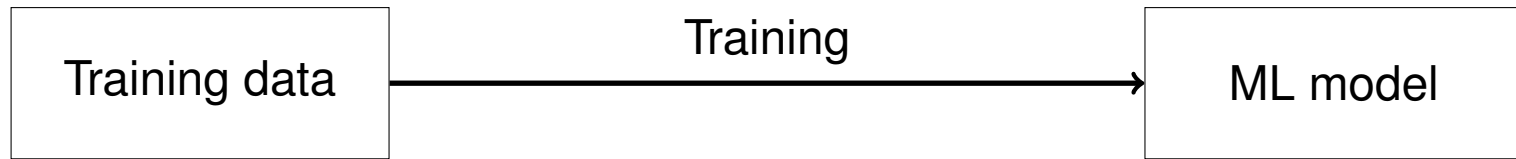
Final Hints

Machine Learning

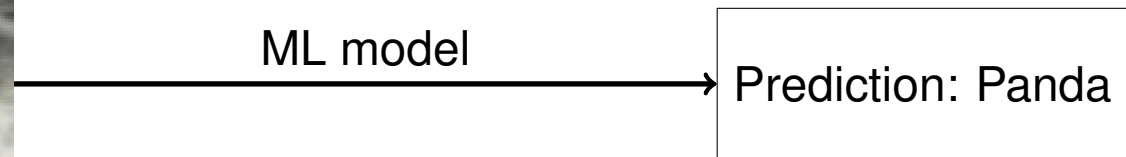


Machine Learning

Machine Learning



Machine Learning



Inference

Adversarial Examples



+ 0.007 ·

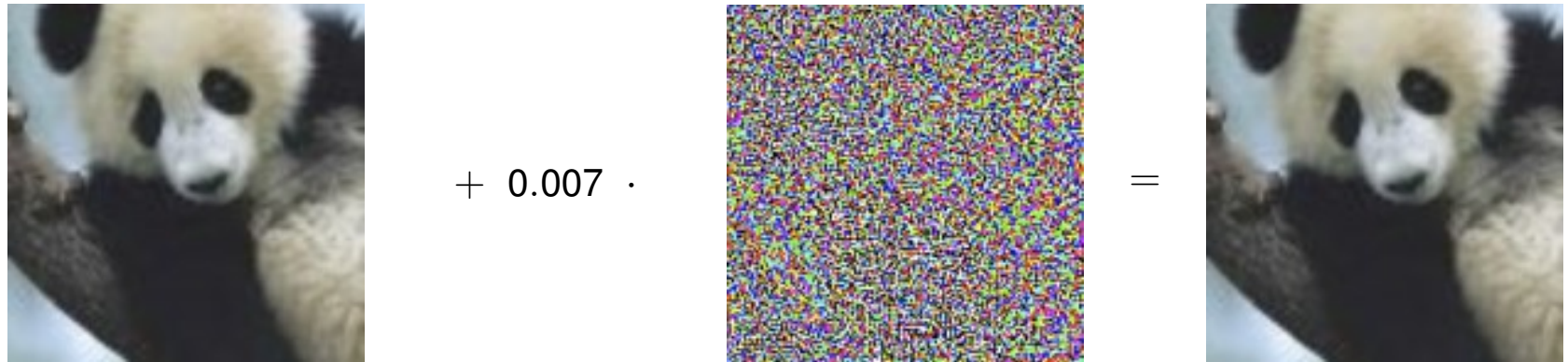


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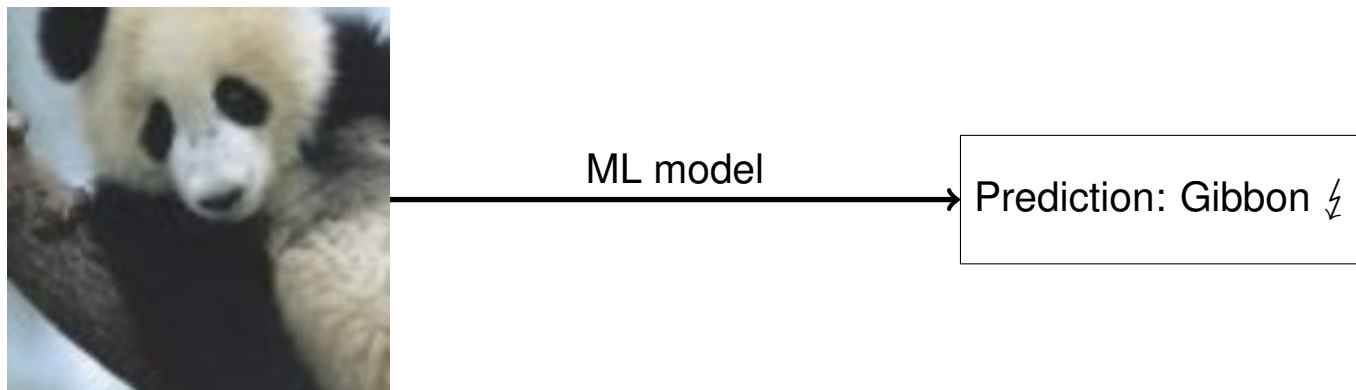


Adversarial Example [Goodfellow 2015]

Adversarial Examples



Adversarial Example [Goodfellow 2015]



Adversarial Attack

Questions

How to

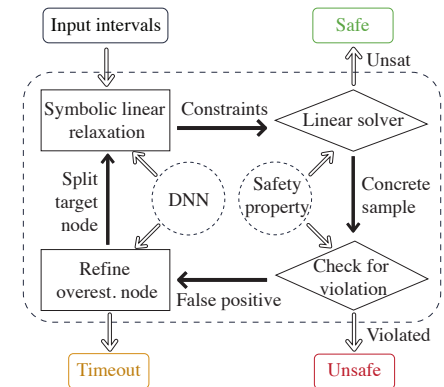
- find adversarial examples if they exist?
- prove that no adversarial examples exist?
- do so automatically?
- do so efficiently (avoid exponential runtime)?

Topics I

1. *Efficient Formal Safety Analysis of Neural Networks*

(Wang et al.) (B/M)

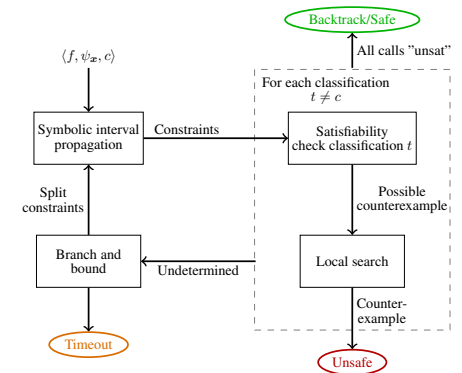
- Describes a toolkit for automatic verification
- Uses symbolic propagation (tracking of dependencies)
- Approximates piecewise linear activation functions



2. *Efficient Neural Network Verification via Adaptive Refinement and Adversarial Search*

(Henriksen, Lomuscio) (M)

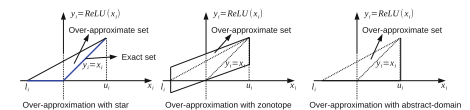
- Describes an improved toolkit
- Can also approximate non-linear functions (sigmoid, tanh)



3. *Star-Based Reachability Analysis of Deep Neural Networks*

(Tran et al.) (M)

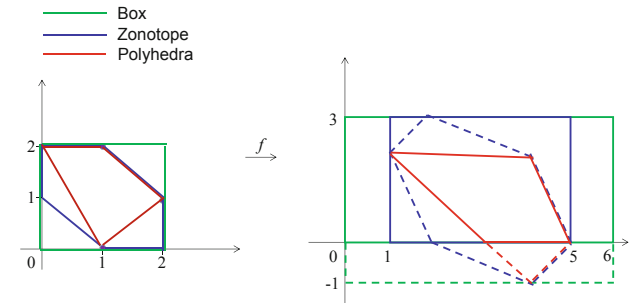
- Describes an alternative approach
- No approximation is needed (sound and complete)
- All (not just one) adversarial examples can be found



Topics II

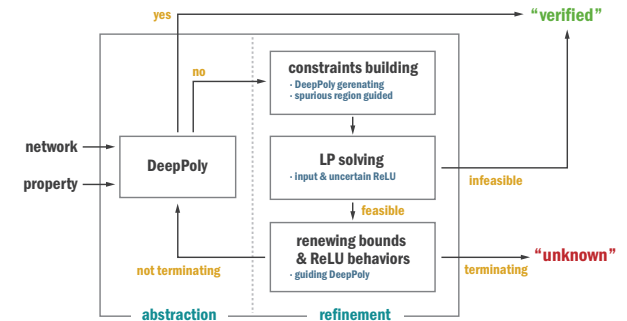
4. *Analyzing Deep Neural Networks with Symbolic Propagation: Towards Higher Precision and Faster Verification* (Li et al.) (B/M)

- Systematic investigation of symbolic domains
- Based on Abstract Interpretation and SMT methods



5. *Improving Neural Network Verification through Spurious Region Guided Refinement* (Yang et al.) (B/M)

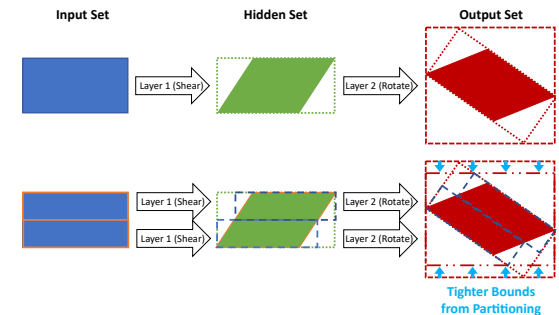
- Elimination of spurious adversarial examples by linear programming techniques
- Based on DeepPoly framework



6. *Robustness Analysis of Neural Networks via Efficient Partitioning with Applications in Control Systems*

(Everett, Habibi, How) (M)

- Application of propagation and partitioning techniques to control systems



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Final Hints

1. Analysis of Bayesian Networks via Prob-Solvable Loops

Ezio Bartocci, Laura Kovács, Miroslav Stankovic: *Analysis of Bayesian Networks via Prob-Solvable Loops*. ICTAC 2020 (B/M)

- Encoding the following types of BNs as **Prob-solvable loops**

- discrete BNs
- Gaussian BNs
- Dynamic BNs

- Looking into the following problems

- exact inference
- expected number of samples
- sensitivity analysis

Discrete Bayesian Network (disBN)

```
graph TD; S((Sprinkler S)) --> G((Grass Wet G)); R((Rain R)) --> G;
```

CPT for S

	S=0	S=1
R=0	0.4-a	0.6+a
R=1	0.01-b	0.99+b

CPT for R

	R=0	R=1
G=0	0.2	0.8
G=1	0.2	0.8

Conditional Probability Table (CPT) for G

	G=0	G=1
S=0, R=0	0.01	0.99
S=0, R=1	0.25	0.75
S=1, R=0	0.9	0.1
S=1, R=1	0.2	0.8

Encoding disBN as Prob-Solvable Loop

```
real R, S1, S0, S, G11, G10, G01, G00, G, GR;  
real a, b;  
real count=1, continue=1;  
while (true){  
  R := 1 [0.8] 0;  
  S1 := R [0.99+b] 0;  
  S0 := (1-R) [0.6+a] 0;  
  S := S0 + S1;  
  G00 := (1-R)*(1-S) [0.99] 0;  
  G10 := R*(1-S) [0.75] 0;  
  G01 := (1-R)*S [0.1] 0;  
  G11 := R*S [0.8] 0;  
  G := G00+G10+G01+G11;  
  GR := G * R;  
  continue := continue * (1-G);  
  count := count + continue;  
}
```

Q1 - Exact Inference Problem

What is the probability that it is raining, given the evidence that grass is wet (with $a=b=0$) ?

$$\mathbb{P}(R | G) = \frac{\mathbb{E}[GR]}{\mathbb{E}[G]} = \frac{0.6396}{0.7308} = 0.8752$$

Q2 - Expected Number of Samples

What is the expected number of samples till an accepting sample occurs (given the evidence that the grass is wet) ?

$$\mathbb{E}[\text{count}_a] = \frac{1 - (0.178a - 0.04b + 0.2692)^n}{-0.178a + 0.04b + 0.7308}$$
$$\#samples = \lim_{n \rightarrow \infty} \mathbb{E}[\text{count}_a] = \frac{1}{-0.178a + 0.04b + 0.7308}$$

Q3 - Sensitivity Analysis

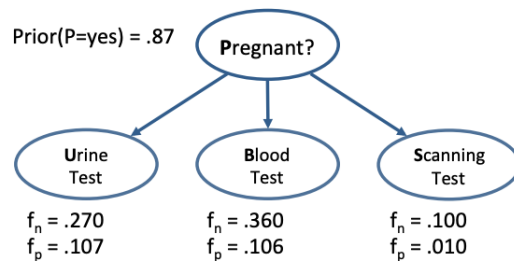
How much the probability that it is raining, given the evidence that grass is wet, is sensitive to small changes (a and b) in some of the BN parameters ?

$$\mathbb{P}(R | G) = \frac{0.04b + 0.6396}{-0.178a + 0.04b + 0.7308}$$

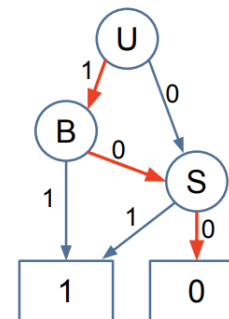
2. Formal Verification of Bayesian Network Classifiers

Andy Shih, Arthur Choi, Adnan Darwiche: *Formal Verification of Bayesian Network Classifiers*. PGM 2018 (B/M)

- Compiling Bayesian network classifiers into **Ordered Decision Diagrams**
- Verifying BN classifiers using ODDs
 - *monotonicity checking*
 - *finding irrelevant features*
 - *verifying classification robustness*
 - *verifying If-Then rules and decision independence*



(a) A naive Bayes classifier

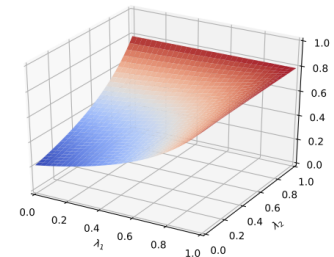


(b) An OBDD

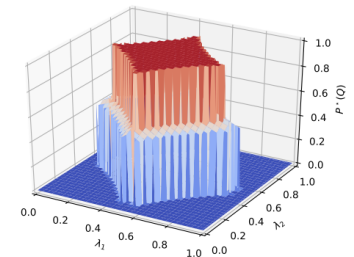
3. On the Relative Expressiveness of Bayesian and Neural Networks

Arthur Choi, Ruocheng Wang, Adnan Darwiche: *On the Relative Expressiveness of Bayesian and Neural Networks*. Int. J. Approx. Reason. 2019 (M)

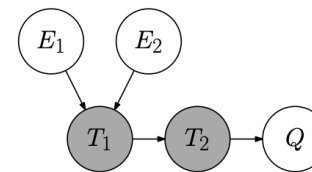
- Reviewing **class of functions** induced by neural and Bayesian networks
- Identifying the corresponding gap in **expressiveness**
- Proposing a new class of Bayesian networks, namely **Testing Bayesian Networks**
- Investigating **expressiveness of TBNs**



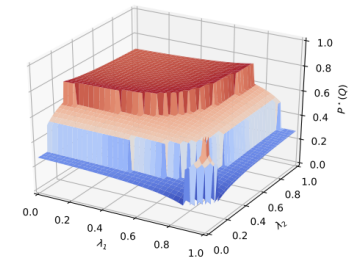
(a) BN function



(b) TBN function



(c) BN/TBN structure



(d) TBN function

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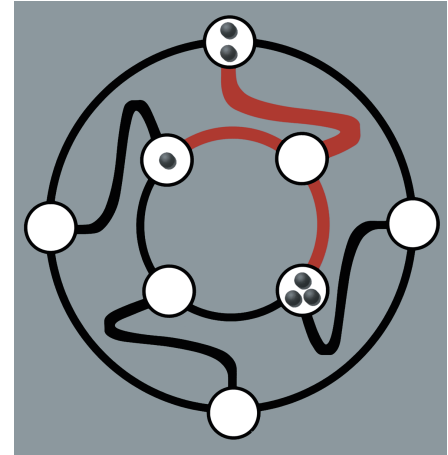
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Final Hints

Quantitative Loop Invariants

- Reasoning about loops is the **hardest task** in (probabilistic) program verification.
- “Practical” approach: capture the loop effect by an **invariant**^a.
- But** how to (automatically) find an appropriate loop invariant?
 - Constraint solving-based numerical approach:
Feng Y. *et al.*: *Finding Polynomial Loop Invariants for Probabilistic Programs*. ATVA 2017. (M)
 - Martingale-based symbolic method:
Barthe G. *et al.*: *Synthesizing Probabilistic Invariants via Doob’s Decomposition*. CAV 2016. (M)
 - Moment-based approach by solving recurrences:
Bartocci E. *et al.*: *Automatic Generation of Moment-Based Invariants for Prob-Solvable Loops*. ATVA 2019. (M)



©A. McIver & C. Morgan, 2005

^aA loop invariant is a property of a loop that is true before and after each iteration.

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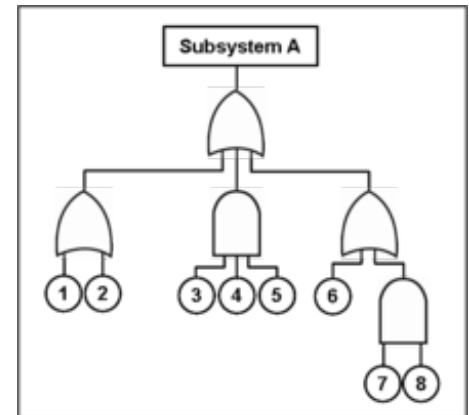
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Formal Approaches to Systems Engineering

- Goal: ensure **Reliability, Availability, Maintainability, and Security (RAMS)** of (computer) systems
- **Fault Trees** as popular modelling formalism of RAMS-domain
- Use of formal methods to analyse fault trees
- Specifically: **probabilistic model checking**
- Doing this efficiently is a challenge
- Topics:
 1. Bäckström et al.: *Effective Static and Dynamic Fault Tree Analysis*. SAFECOMP 2016 (B)
 - presents efficient static and dynamic analyses of dynamic fault trees
 2. Kordy et al.: *Attack-Defense Trees*. J. Log. Comput. 24, 2014 (B)
 - surveys various usage scenarios and semantics for attack-defence scenarios for security applications
 3. Aslanyan et al.: *Quantitative Verification and Synthesis of Attack-Defence Scenarios*. CSF 2016 (B/M)
 - translates attack defence trees to two-player games to enable their stochastic analysis



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Some Final Hints

Hints

- Take your time to **understand** your literature.
- Be **proactive**! Look for **additional** literature and information.
- Discuss the content of your report with other students.
- Be **proactive**! Contact your supervisor **on time**.
- **Prepare** the meeting(s) with your supervisor.
- Forget the idea that you can prepare a talk in a day or two.

We wish you success and look forward to an enjoyable and high-quality seminar!