# Nuclear Medicine, Treatment of Thyroid Cancer and Mathematical Modelling

Ladislav Jirsa

ÚTIA, Academy of Sciences
Praha, Czech Republic

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# Outline of Talk

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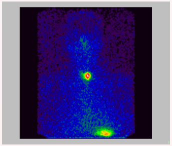

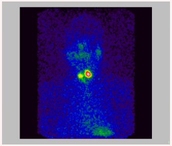

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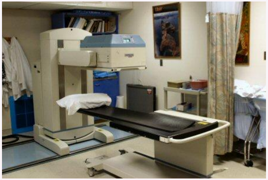
$\gamma$-camera (matrix of probes)



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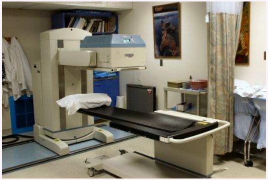

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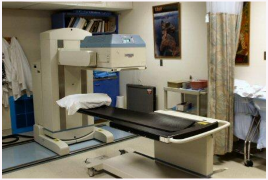

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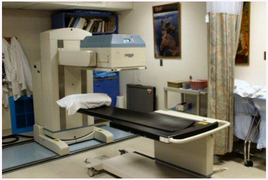

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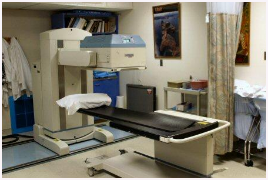

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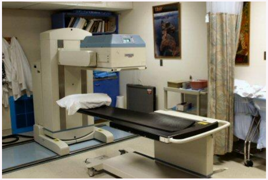

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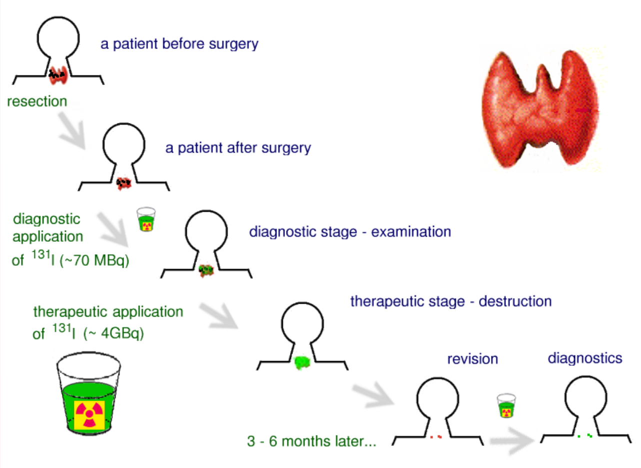
- focus on treatment of thyroid diseases

# Treatment Schedule after Thyroid Cancer Diagnosis



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Uncertainty does not significantly decrease with repeated calibration

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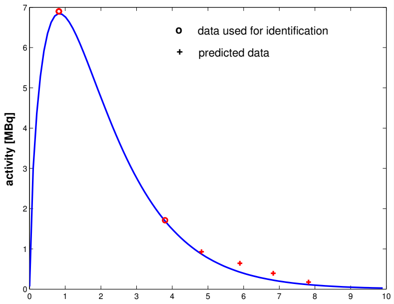


Typical data $\mathcal{D}_n \equiv \{(t_i, A_i)\}_{i=1}^n$

| $i$ | time $t_i$ [days] | estd. activity $A_i$ [MBq] |
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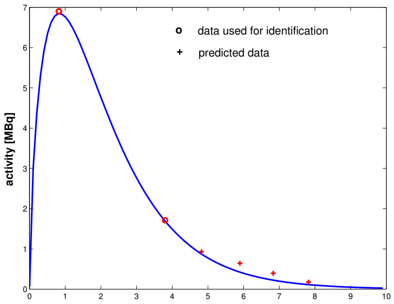


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- Marginal posterior pdf $f(k|\mathcal{D}, \mathcal{I}_c, \mathcal{I}_0)$: Student

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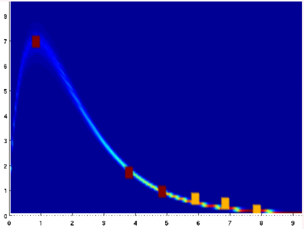

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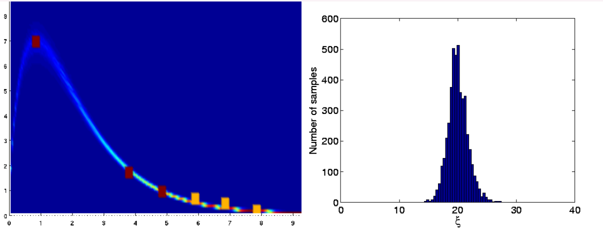

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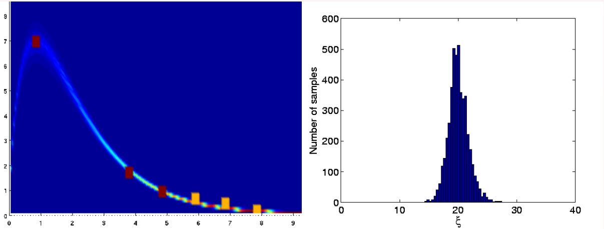


Empirical $f(\xi)$ approximated by log-normal with sufficient precision

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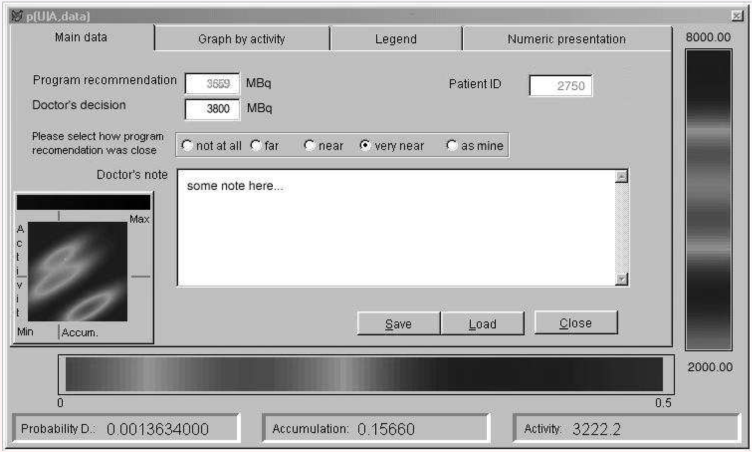
- call the advisory procedure to generate an individual recommendation of activity

# GUI for the Advisory System



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Only dosimetric data included in mixture processing

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- other than medical data are being gathered for off-line processing

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