Uncertainty in multitask learning: joint representations for probabilistic MR-only radiotherapy treatment planning

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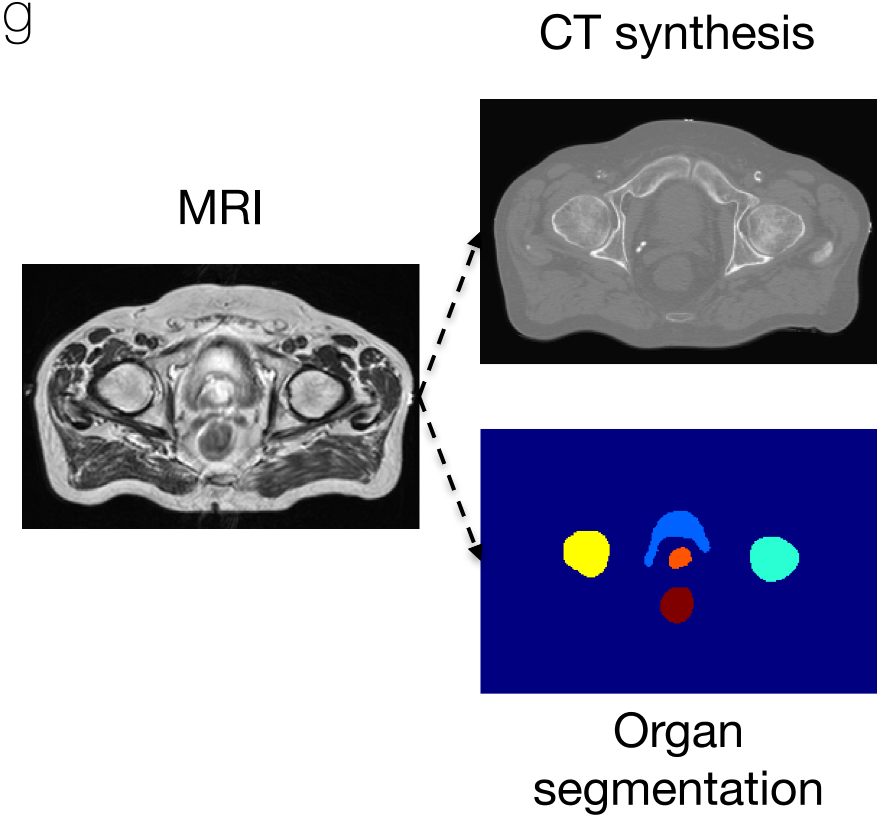
MR-only radiotherapy treatment planning

- MR-only radiotherapy treatment planning requires the simultaneous
  a) synthesis of a CT scan (synCT) from MRI
  b) segmentation of organs at risk (OAR) from MRI

- Main goal
  a) Multi-task learning for simultaneous regression and segmentation
  b) Probabilistic deep learning to acquire uncertainties in the prediction of the network



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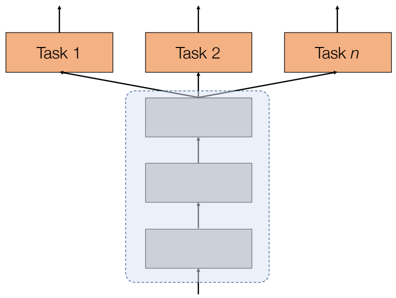
Multi-task feature learning



- Medical image analysis aims to learn a **common anatomical representation**
- Learn a non-linear mapping from this feature space to minimise a loss
- *How to minimise this loss in a multi-task setting?*

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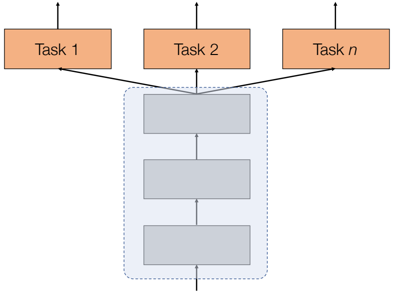

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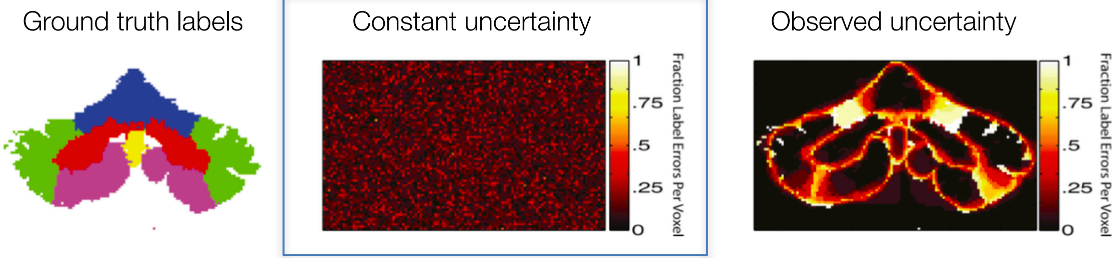

Figure adapted from Asman *et. al.*, IEEE TMI 2011

- Allows us to exploit this property (heteroscedasticity) for a natural mechanism for weighting task losses

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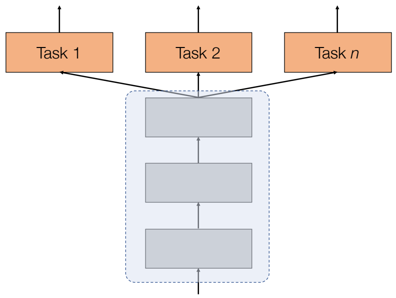
Multi-task feature learning



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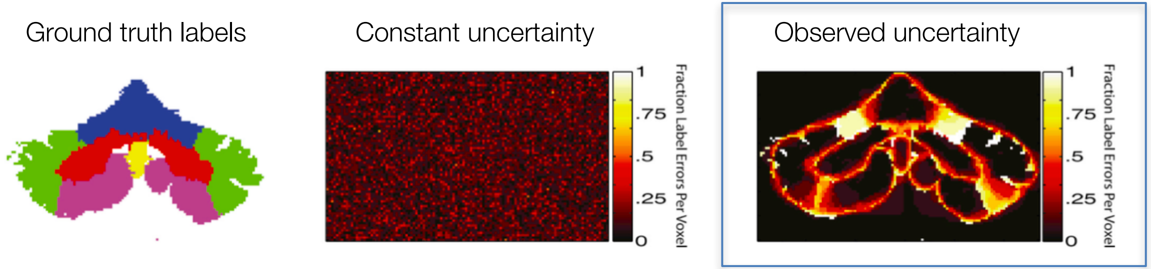

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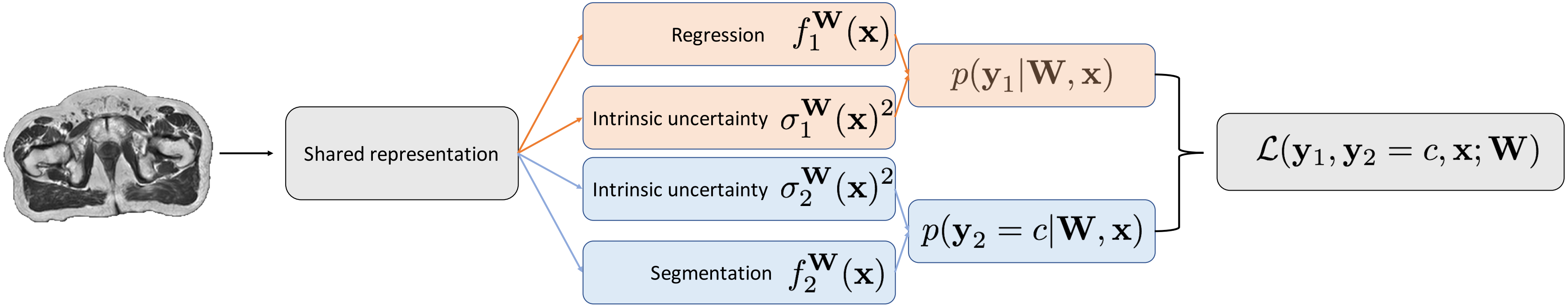
Our contribution

- Probabilistic dual-task network with hard-parameter sharing
    - Shared representation network + regression and segmentation specific branches
- Predict task-specific heteroscedastic uncertainty for spatially adaptive task loss weighting
- Approximate Bayesian inference to also capture uncertainty in the model weights



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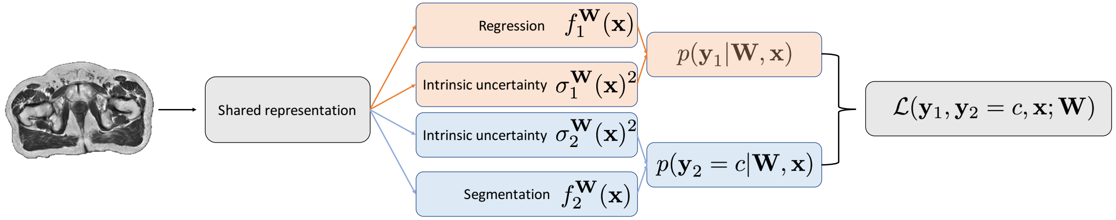
Our contribution

- Multi-task likelihood:

$$\mathcal{L}(\mathbf{y}_1, \mathbf{y}_2 = c, \mathbf{x}; \mathbf{W}) = \frac{||\mathbf{y}_1 - f_1^{\mathbf{W}}(\mathbf{x})||^2}{2\sigma_1^{\mathbf{W}}(\mathbf{x})^2} + \frac{\mathrm{CE}(f_2^{\mathbf{W}}(\mathbf{x}), \mathbf{y}_2 = c)}{2\sigma_2^{\mathbf{W}}(\mathbf{x})^2} + \log\left(\sigma_1^{\mathbf{W}}(\mathbf{x})^2 \sigma_2^{\mathbf{W}}(\mathbf{x})^2\right)$$

- Separate networks to predict:
  - Regression and segmentation per voxel: $f_1^{\mathbf{W}}(\mathbf{x})$, $f_2^{\mathbf{W}}(\mathbf{x})$
  - Spatially adaptive weighting using heteroscedastic uncertainty: $\sigma_1^{\mathbf{W}}(\mathbf{x})^2$, $\sigma_2^{\mathbf{W}}(\mathbf{x})^2$



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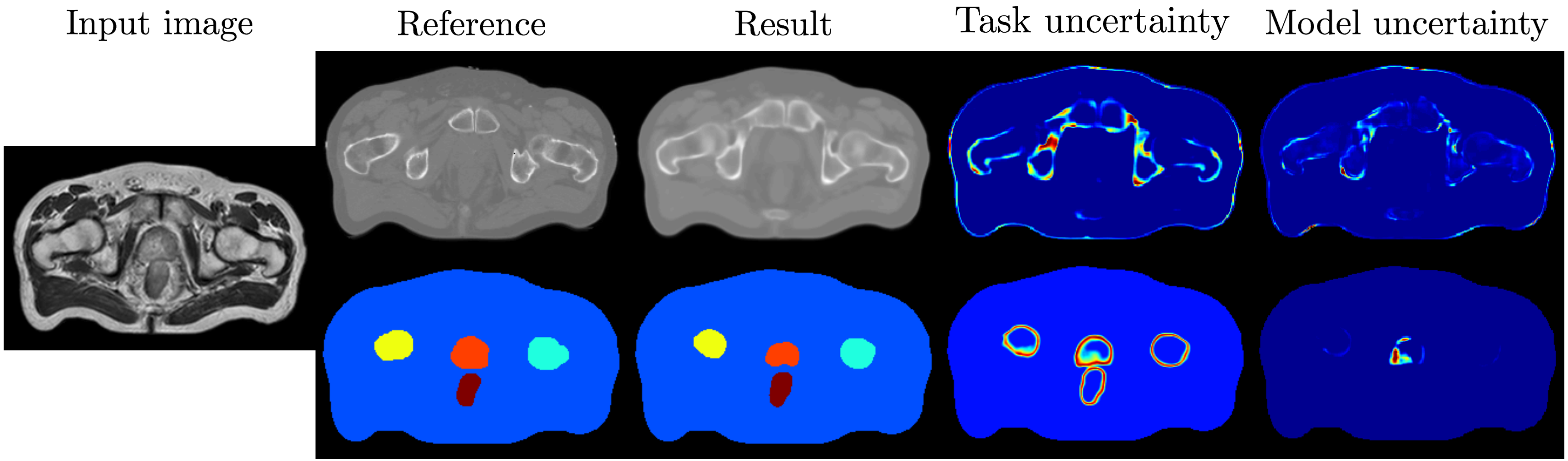
Experiment on 15 prostate cancer patients

- 3-fold cross-validation for training and testing



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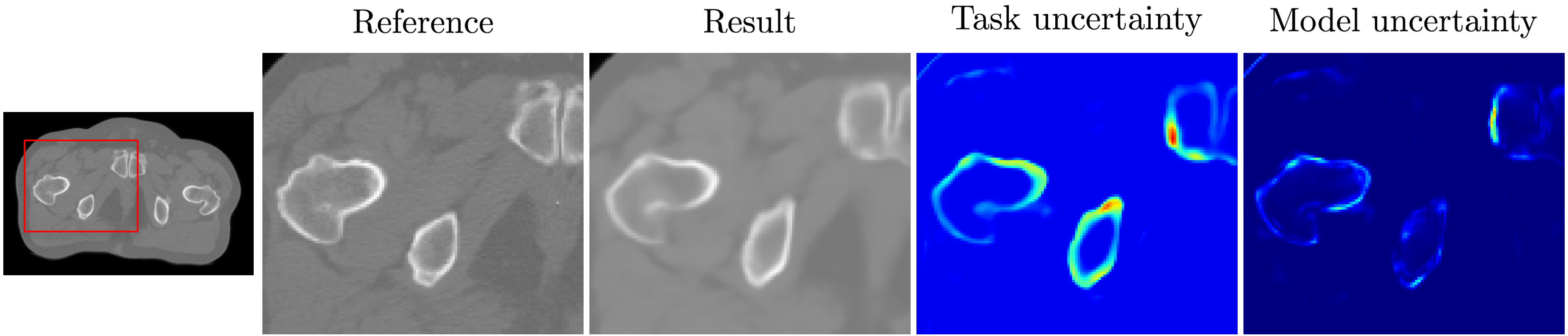

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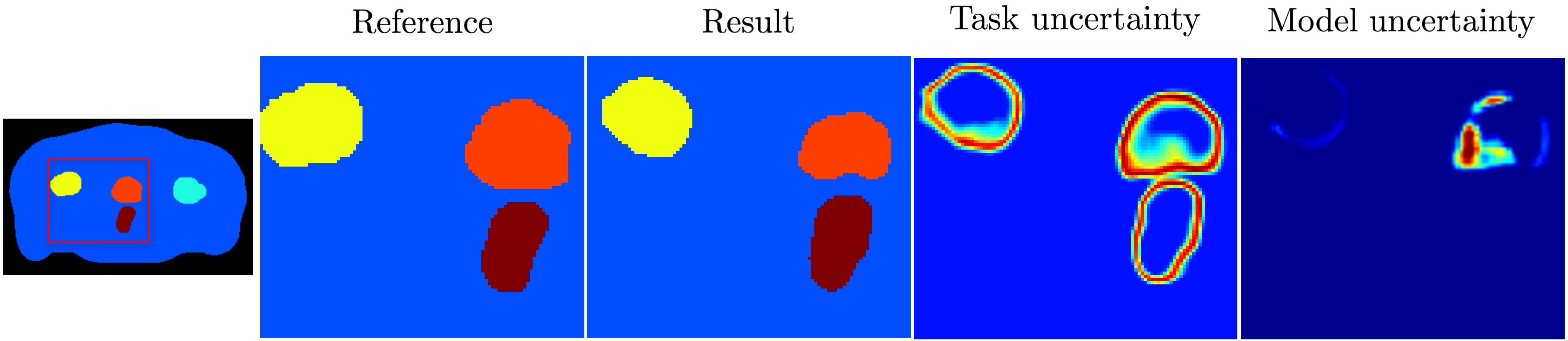

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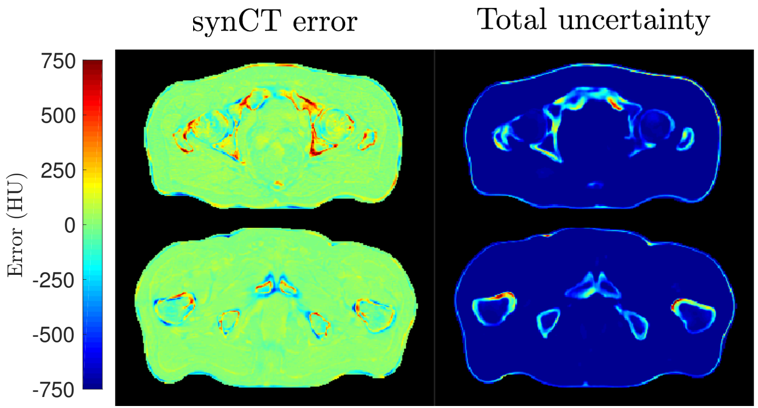
Main results

1. Joint modelling of heteroscedastic uncertainty and test-time variance in a multi-task setting **outperforms** homoscedastic weighting and all other models

Models	All	Bone	L femur	R femur	Prostate	Rectum	Bladder
Regression - synCT - Mean Absolute Error (HU)							
Multi-task + homoscedastic weighting	44.3(3.1)	126(14.4)	74.0(19.5)	73.7(17.1)	29.4(4.7)	58.4(48.0)	18.2(3.5)
Our method	43.3(2.9)	121(12.6)	69.7(13.7)	67.8(13.2)	28.9(2.9)	55.1(48.1)	18.3(6.1)

2. Total uncertainty provides a mechanism for automated quality control and assurance



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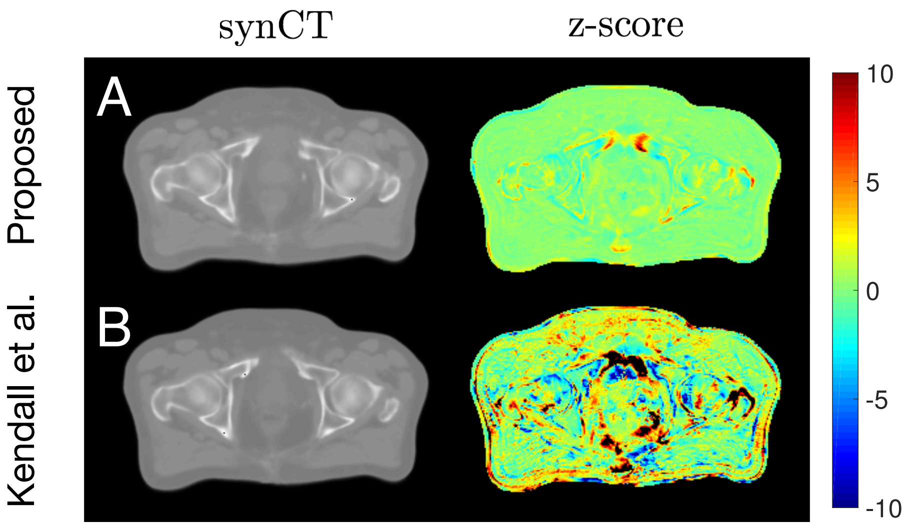
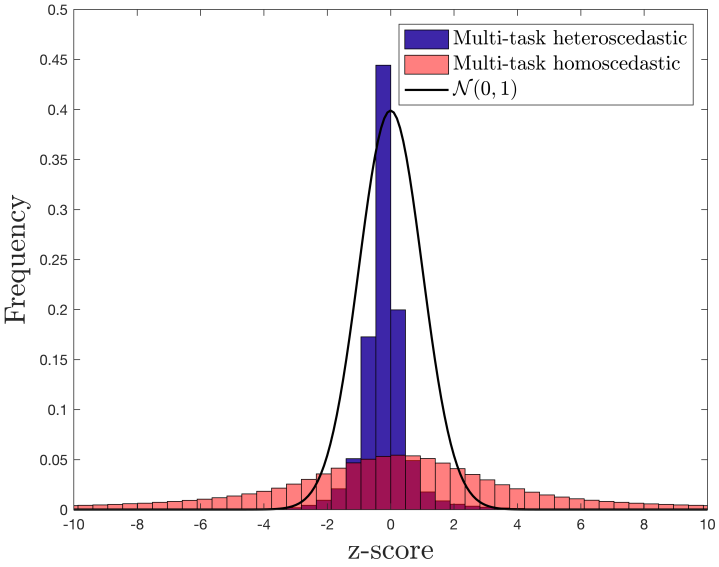
Main results

- Well calibrated variance from our model (**A**) compared those with constant task uncertainty (**B**)





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Thanks!

- More results in poster!
- Code to be released within NiftyNet (pip install niftynet)
- Poster #101 tonight from 18:00 to 19:30!

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