Multi-Task Minimum Error Rate Training for SMT

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- Predestined application: Patent translation over classes of patents w.r.t. International Patent Classification (IPC)
  - **commonalities:** highly specialized legal jargon not found in everyday language, rigid textual structure including highly formulaic language.
  - **differences:** technological terminology specific to IPC class.

IPC Sections

- A Human Necessities
- B Performing Operations; Transporting
- C Chemistry; Metallurgy
- D Textiles; Paper
- E Fixed Constructions
- F Mechanical Engineering; Lighting; Heating; Weapons; Blasting
- G Physics
- H Electricity

Goal and Approach

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Approach: Machine learning approach to trading off optimality of parameter vectors for each task-specific model and closeness of these model parameters to average parameter vector across models.

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- In other words: How much gain is there in extending the standard tuning technique of minimum error rate training (MERT) to **multi-task MERT** for SMT.
- Also apply techniques for parameter averaging from distributed learning to a version of **averaged MERT**.

Parallel Patent Data

- MAREC: 19 million patent applications and granted patents, standardized format from four patent organizations (European Patent Office (EP), World Intellectual Property Organisation (WO), United States Patent and Trademark Office (US), Japan Patent Office (JP)), from 1976 to 2008.

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Distribution of IPC sections for de-en abstracts and claims

A	266,521	21.81%
B	384,517	31.47%
C	372,903	30.52%
D	50,579	4.14%
E	54,396	4.45%
F	149,370	12.22%
G	291,671	23.87%
H	228,147	18.67%

Parallel data for de-en patent translation

	train	dev	devtest	test
# parallel sents	1M	2K	2K	2K
avg. # tokens de	32,329,745	59,376	60,061	59,930
avg. # tokens en	36,005,763	69,584	70,700	70,331
year	1993-1995	2007	2008	2008

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$$\min_{w_1,\dots,w_D} \sum_{d=1}^{D} l_d(w_d) + \lambda \sum_{d=1}^{D} \|w_d - w_{\text{avg}}\|_p^p \qquad (1)$$

Multi-task prediction

Prediction:

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Task-specific weight vectors $w_d \in \{w_1, \ldots, w_D\}$ that have been adjusted to trade off task-specificity (small λ) and commonality (large λ).

or: Average weight vector w_{avg} as a global model.

Average MERT


```
AvgMERT(w^(0), D, {c_d}_{d=1}^D):
for d = 1, ..., D parallel do
    for t = 1, ..., T do
        w_d^(t) = MERT(w_d^(t-1), c_d(w_d))
    end for
end for
return w_avg = 1/D sum_{d=1}^D w_d^(T)
```

$\texttt{AvgMERT}(w^{(0)}, D, \{c_d\}_{d=1}^{D})$:
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  end for
end for
return $w_{\text{avg}} = \frac{1}{D} \sum_{d=1}^{D} w_d^{(T)}$

- Apply ideas from distributed learning (Zinkevich et al. NIPS'10) by basing the distribution strategy on task-specific partitions of data.

Multi-task MERT

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code: Script wrapper around the `MERT` implementation of Bertoldi et al. 2009; licensed unter the LGPL; online at `http://www.cl.uni-heidelberg.de/statnlpgroup/mmert/`.

Multi-task MERT

$\texttt{MMERT}(w^{(0)}, D, \{c_d\}_{d=1}^{D})$:

for $t = 1, \ldots, T$ **do**

  $w_{\text{avg}}^{(t)} = \frac{1}{D} \sum_{d=1}^{D} w_d^{(t-1)}$

  for $d = 1, \ldots, D$ **parallel do**

    $w_d^{(t)} = \texttt{MERT}(w_d^{(t-1)}, c_d(w_d))$

    for $k = 1, \ldots, K$ **do**

      if $w[k]_d^{(t)} - w_{\text{avg}}^{(t)}[k] > 0$ **then**

        $w_d^{(t)}[k] = \max(w_{\text{avg}}^{(t)}[k], w_d^{(t)}[k] - \lambda)$

      else if $w_d^{(t)}[k] - w_{\text{avg}}^{(t)}[k] < 0$ **then**

        $w_d^{(t)}[k] = \min(w_{\text{avg}}^{(t)}[k], w_d^{(t)}[k] + \lambda)$

      end if

    end for

  end for

end for

return $w_1^{(T)}, \ldots, w_D^{(T)}, w_{\text{avg}}^{(T)}$

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- `AvgMERT` and `MMERT` are algorithms described above.
- w_{avg} is global model produced as by-product in multi-task learning.

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- statistically significant improvement over *pooled* indicated by $+$
- statistically significant improvement over `AvgMERT` indicated by $\#$

Experimental Results

section	*ind.*	*pooled*	AvgMERT	MMERT	w_{avg}
A	0.5187	0.5199	**0.5213***	0.5195$^{\#}$	0.5196$^{\#}$
B	0.4877	0.4885	0.4908^{*+}	0.4911*	**0.4921**$^{*\#}$
C	0.5214	0.5175	0.5199^{*+}	**0.5218**$^{\#}$	0.5162$^{*\#}$
D	0.4724	0.4730	0.4733	**0.4736**	0.4734
E	0.4666	0.4661	0.4679^{*+}	0.4669	**0.4685***
F	0.4794	0.4801	0.4811*	0.4821*	**0.4830**$^{*\#}$
G	0.4596	0.4576	0.4607^{+}	0.4606	**0.4610***
H	0.4573	0.4560	0.4578	**0.4581**	**0.4581**

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- Best results are small, but statistically significant improvements over *ind.* and *pooled*.
- Significant degradation on section C ("chemistry") by averaging techniques due to expeptional character of chemical formulae and compound names.
- Interpretation of small improvements with a grain of salt, however, hope for larger improvments with larger feature sets.