A Bootstrapped Model to Detect Abuse and Intent in White Supremacist Corpora

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Abstract—Intelligence analysts face a difficult problem: distinguishing extremist rhetoric from potential extremist violence. Many are content to express abuse against some target group, but only a few indicate a willingness to engage in violence. We address this problem by building a predictive model for intent, bootstrapping from a seed set of intent words, and language templates expressing intent. We design both an n-gram and attention-based deep learner for intent and use them as colearners to improve both the basis for prediction and the predictions themselves. They converge to stable predictions in a few rounds. We merge predictions of intent with predictions of abusive language to detect posts that indicate a desire for violent action. We validate the predictions by comparing them to crowd-sourced labelling. The methodology can be applied to other linguistic properties for which a plausible starting point can be defined.

I. INTRODUCTION

Intelligence analysts scan online data looking for the signals of those who plan to carry out violent attacks. Several models have been developed for what might be called “violent thought” in islamist and white supremacist forums. Detecting when violent thought transforms into violent action is more problematic. There are many examples of so-called “armchair jihadists” who post extensively but never do anything; and conversely those who move very rapidly to violent action without extensive discussion (for example, Farhad Khalil Mohammad Jabar, who killed an Australian civilian police employee apparently within hours of hearing a radical islamist talk).

Models that detect abusive language and hate speech are moderately well developed. We expand their power by adding the capability to detect intent. Intent can be defined as “the state of mind of one who aims to bring about a particular consequence” [8]; when tied to abusive language, this acts as a signature for those who are most likely to carry out violent actions. Intelligence analysts can use this abusive intent model to focus attention on those whose posts make them of greatest concern.

Datasets labelled by intent do not exist (except perhaps in classified environments). We design a bootstrapped approach that starts from small, widely-agreed signals of intent from the literature; and then bootstraps these into a pair of models, one using n-grams and one using biLSTMs, to predict intent. These are coupled with a deep-learning model of abusive language to label posts in White Supremacist settings by their abusive intent. The intent model’s predictions were compared to labels generated by human volunteers, with more than 80% agreement.

II. RELATED WORK

Linguistic understanding of intent begins with the work of Leech [17] who observed that will and going to are the strongest signals of the “future as outcome of present” [16]. However, a distinction must be drawn between the future as an outcome of present circumstances, or present intentions, and so the author’s stance with respect to these verbs is critical. In particular, the presence of first-person pronouns distinguishes intent from observation. Frame analysis examines the effect of communication on audiences, and has been used by Sanfilippo [21] to assess the likelihood of violent action from online posts. This approach has been partially automated [22].

Intent has also been considered as a social process. The relationship between an in-group and an out-group has been leveraged to detect abusive language, and also to understand and characterise threats [26]. The cooccurrence of abusive language and intent has been observed to be associated with violent actions [1, 18, 24, 25].

Detection of properties of interest in natural language either uses bag-of-words approaches, or deep learning, mostly using biLSTMs. Intent detection has previously been studied in the context of business interactions: what is this (potential) customer trying/planning to do [3, 4, 9, 10, 14, 28]. Others have built models to detect intent in wider contexts such as forums using patterns such as actionable verb object [27]; or regular expressions I . . . want . . . to . . . [20]. The definition of intent used by these approaches is quite broad.

The detection of abusive language has been well-studied [5, 6, 15, 29] using both bag-of-words and deep-learning approaches, with typical accuracies in the 90% range.

A technique on which we build, called double bootstrapping, was developed by Gao et al. [7]. For unlabelled datasets, it begins from a small dictionary of hate-speech terms, generates initial labels for the data, feeds these into two models, which then co-train, each learning from the labels, making
new predictions, and then passing the predictions to the other model.

III. METHODOLOGY

Three White Supremacists forums were used as datasets: Stormfront, Iron March, and the manifesto of the New Zealand attacker in 2019. As well, a Wikipedia dataset was used as a contrast set, and an abusive language dataset used to train a predictor for abuse.

Forum posts are noisy natural language, with misspellings and typos, in-group language, and non-textual elements such as emojis. Each dataset was processed to remove quotations (detected from html tags), user handles, html tags, emojis, and Unicode characters. Hashtags were replaced by their content, divided into words if camel case was used; characters repeated more than twice were replaced by two occurrences.

Table I shows the effect of preprocessing. The reduction in size for Stormfront reflects the large number of quotations typically used, both from the other posts and from media web sites.

TABLE I: Dataset character lengths before and after processing

| Dataset            | Unprocessed | Processed | Removed |
|--------------------|-------------|-----------|---------|
| Storm-Front (intent) | 252,908,165 | 141,192,145 | 44.1%   |
| Wikipedia (intent)  | 63,228,684  | 6,037,240  | 96.5%   |
| Abuse ensemble      | 91,742,800  | 87,291,993 | 4.6%    |
| Iron March          | 9,668,405   | 7,827,782  | 19.0%   |
| Manifesto           | 98,642      | 96,782     | 1.9%    |

Documents were split into segments, broken at sentence boundaries or semicolons. Segments are the primary units for which predictions of intent and abuse will be made.

A segment by word n-gram frequency matrix was created, using $n = 3$ to 6. Examination of the cumulative frequency indicated that almost nothing was lost by taking only the 500,000 most common n-grams.

Embeddings for the data from Stormfront were created using FastText 0.9.2 [2] to produce 200-dimensional vectors, using skipgram with default training parameters. The training process took roughly 5 days.

Deriving an embedding from the Stormfront dataset, rather than using the generic embedding, shows the importance of in-group language patterns. Table II shows the neighbours of “liberal” in the generic FastText embedding, while Table III shows the neighbours in the embedding derived from Stormfront. The default embedding shows a conventional political view of “liberal” while the customised embedding shows a much more doctrinaire view.

A. Intent label inference

Datasets labelled with intent are not publicly available, so we develop a way of inferring intent labels by bootstrapping. The first step is to develop a template for expressing intent. The basic structure of the template is: first-person pronoun, desire verb (“going to”, “will”), action verb (“fight”) and optionally a target and timing. The template elements must occur in the appropriate order and relationships. Figures 1 and 2 and Tables IV and V provide examples.

Segments from the dataset are parsed using the spaCy statistical parser [11] which is able to handle the variability of online documents, including misspellings. It produces POS tags and dependencies.

Initial labels for each segment are generated as follows: if it contains a match for the template, it is labelled +1; if it contains a negation question, or a second- or third-person

### TABLE II: 25 words closest to “liberal” in default FastText embeddings [19]

| Word          | Cosine distance |
|---------------|-----------------|
| conservative  | 0.8223          |
| liberals      | 0.799999        |
| leftist       | 0.792378        |
| ultra-liberal | 0.768488        |
| left-liberal  | 0.763355        |
| hyper-liberal | 0.762267        |
| right-wing    | 0.754539        |
| left-wing     | 0.75325         |
| left-wing     | 0.752645        |
| non-liberal   | 0.751433        |
| conservatives | 0.751097        |
| liberalist    | 0.730335        |
| liberalian    | 0.750089        |
| moderate-liberal | 0.748242 |
| libertarian   | 0.745923        |
| left-leaning  | 0.742489        |
| liberal       | 0.738087        |
| ultraliberal  | 0.725314        |
| rightwing     | 0.721381        |
| liberal-minded| 0.715108        |
| centrist      | 0.714085        |
| pro-liberal   | 0.713632        |
| liberal-progressive | 0.712557 |
| pseudo-liberal| 0.705708        |
| super-liberal | 0.705055        |

### TABLE III: 25 words closest to “liberal” in customised FastText embedding built from Stormfront

| Word          | Cosine distance |
|---------------|-----------------|
| gliberal      | 0.822855        |
| leftist       | 0.814352        |
| liberalist    | 0.803048        |
| liberal       | 0.792378        |
| multiculturalist | 0.792877 |
| libard        | 0.791708        |
| leaningliberal| 0.791068        |
| ultraliberal  | 0.784252        |
| libarded      | 0.77373         |
| liberal       | 0.763863        |
| lefty         | 0.762339        |
| liberalistic  | 0.760414        |
| liberals      | 0.758157        |
| liberal       | 0.757605        |
| liberal       | 0.757185        |
| conservatives | 0.736382        |
| multiculturalist | 0.741517 |
| liberal       | 0.739852        |
| ultraliberals | 0.739685        |
| oziberal      | 0.738213        |
| liberal-minded| 0.737438        |
| egalitarian   | 0.735231        |
| multiculturalist | 0.734759 |
| liberal       | 0.734605        |
| justiberal    | 0.734268        |
TABLE IV: Components of the short form intent template

| Role                  | Parent       | Relationship to parent |
|-----------------------|--------------|------------------------|
| Pronoun               | Action verb  | Nominal subject        |
| Desire verb           | Action verb  | Auxiliary              |
| Action verb           | None         | N/A                    |
| Target (Optional)     | Action verb  | Direct object          |
| Timing (Optional)     | Action verb  | Noun phrase as adverbial modifier |

TABLE V: Components of the long form intent template

| Role                  | Parent       | Relationship to parent |
|-----------------------|--------------|------------------------|
| Pronoun               | Verb         | Nominal subject        |
| Desire                | None         | N/A                    |
| To                    | Action verb  | Auxiliary              |
| Action verb           | Desire verb  | Open clausal complement |
| Target (Optional)     | Action verb  | Direct object          |
| Timing (Optional)     | Action verb  | Noun phrase as adverbial modifier |

The process is initialised from a seed set of “obvious” desire verbs: “want”, “need”, “going”, “have”, “about”, “planning”, and “will”. The embedding is treated as a vector space and verbs derived hypercone prism based on the seven initial vectors are treated as a strong desire verbs. To be included, the unnormalized cosine similarity of a selected desire verb must be less than twice the distance to the mean of the seed set. This produces 596 desire verbs, including verbs such as “seek” and “aiming”. 95.3% of the segments initially labelled as intentful still qualify.

The initial label generation phase, applied to the segments from Stormfront and Wikipedia labelled 1.4% as intentful, 29.1% as non-intentful, and 69.5% as undetermined. As expected, all of the Wikipedia segments were labelled as non-intentful.

The set of desire verbs is now refined. This requires both expansion so that misspellings and other variants are captured; and restriction so that only strong desire verbs remain. Fortunately, using the geometry of the embedding space solves both problems.

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TABLE VI: Components of the long form intent template

| Role                  | Parent       | Relationship to parent |
|-----------------------|--------------|------------------------|
| Pronoun               | Verb         | Nominal subject        |
| Desire                | None         | N/A                    |
| To                    | Action verb  | Auxiliary              |
| Action verb           | Desire verb  | Open clausal complement |
| Target (Optional)     | Action verb  | Direct object          |
| Timing (Optional)     | Action verb  | Noun phrase as adverbial modifier |

B. Bootstrapping using two concurrent learners

The model is based on two learners: an n-gram based learner; and a deep learner that uses the FastText embeddings and a BiLSTM-attention architecture [23, 31]. These are used in parallel, and the results of each better inform the signals of intent for the next round.

1) n-gram learner: Assume that we have a set of label values between 0 and 1 for the segments; (initially this is obtained from the template matching). The n-gram predictor first assigns a score to each n-gram based on the ratio of how often it occurs in segments whose label is greater than 0.5 versus how often it occurs in segments whose label is less than 0.5, both frequencies normalized by the number of such segments in which it is present. n-grams in the 99.9th percentile of ratio values in either direction are considered predictive of intent or non-intent.

Segments are labelled as intent if they contain only intentful n-grams; as non-intent if they contain only non-intentful n-grams, but unlabelled if both or neither happen to be present.

2) Deep learner: In parallel, a deep learner using a bi-LSTM is applied to the segments, knowing the FastText embeddings of each word. The network architecture is shown in Figure VI. The biLSTM begins with a conventional learning phase in which it trains based on a randomly selected set of segments with the labels for each segment rounded to 0 or 1. As it trains the loss contribution from each segment is downweighted by how far its current label is from either 1 or 0.

After this phase, the deep learner then predicts labels for all of the segments, including those without labels. Segments close to the extremes have their scores altered by 10% to make them even stronger.

TABLE VI: biLSTM architecture

| Layer | Units | Input dimension | Output dimension |
|-------|-------|-----------------|------------------|
| BI-LSTM | 200 | 200 × 200 | 200 × 100 |
| Attention | 400 | 200 × 400 | 400 |
| Dense | 50 | 400 | 50 |
| Dense | 1 | 50 | 1 |

3) Merging predictions for the next round: Both learners are trying to increase the number of strong predictions, that is predictions close to 1 or close to 0. However, they are simultaneously learning the natural language signals of intent. To prevent too rapid convergence of labels, each model is limited in how many labels it can present to the merge mechanism.

If the previous round of each model had predicted $n_p$ labels with value 1 and $n_n$ labels with value 0, then at most these numbers of further records can be suggested to the
merge mechanism. In other words, if 100 labels were 1 in the previous round, then at most 200 segments can be presented as 1 to the merge mechanism in the current round.

This limitation on convergence could potentially slow down the overall process when a model quickly discovers the required signals. However, this does not seem to be the case for complex properties such as intent.

The merge mechanism relabels each segment based on the label from either of the models, except if they have contradictory senses (that is, one predicts intent while the other predicts non-intent) in which case the label remains unchanged. If a segment is labelled either 0 or 1, that label is locked and will not change in subsequent rounds.

The number of rounds can be altered for each particular dataset, but 5 or 6 seems to be adequate.

IV. MODELLING ABUSIVE LANGUAGE

There is intrinsic interest in modelling intent, but the applications we envisage are those where intent per se is not interesting (“I’m going to buy her a birthday present”) but where intent associated with abusive language signals the potential for violent action. We must therefore also identify segments that express abuse.

Abusive language detection is a well-studied problem and labelled data is available [15, 31]. We use three relevant datasets: a small set of documents from Stormfront; a corpus from a competition run by Imperium for detecting insults [12]; and a dataset from a competition by Conversation AI to identify multiple types of abusive language in Wikipedia comments [13]. The documents from these datasets were randomly mixed to ensure no sequential structure, creating a dataset with 240,846 samples (Table VII).

| Dataset            | Size   | Abusive Fraction |
|--------------------|--------|------------------|
| Storm-Front        | 10,705 | 11.2 %           |
| Insults            | 6,594  | 20.4 %           |
| Wikipedia comments | 223,549| 9.9 %            |
| Ensemble           | 240,846| 10.4 %           |

A biLSTM predictive model, using the word embeddings derived from Stormfront and the same network as for intent (Table VI).

An 85–15 train-test split (204,719 training segments, 36,127 test segments) was used, with a maximum of 50 epochs, and early stopping with patience 3. The learning rate was 0.001, beta one and two were 0.9 and 0.999, and epsilon was $1 \times 10^{-7}$. This model’s accuracy was 86.7%.

A. Combining intent and abuse scores

Both models produce predictions in $[0, 1]$ and there are multiple ways in which these could be combined. For our application domain, where the primary goal is to identify segments that are high in both intent and abuse, we multiply the two predicted scores. Even moderate scores in either dimension reduce the overall score, focusing attention on segments of greatest practical interest.

B. Scores for documents from scores for segments

Combining scores for segments to produce a single score for each document raises subtle problems. An author may be abusive in one segment and segue into intent in the adjacent one, or vice versa. A document may begin with a discussion of a perceived problem (neither abusive or intentful) and only then begin to express abuse or intent or both.

The approach we chose was to consider the abuse and intent scores of each segment separately, take each set of three adjacent (overlapping) segments in a document, take the maximum abuse score and the maximum intent score in the set of three, and then form the product of these maximums. The overall score for the document is the maximum of these products over all of the three-segment windows.

V. PERFORMANCE AND VALIDATION

In each epoch of intent training, the sequence learner and the deep learner are run in parallel, and then a consensus is derived. Table VIII shows some of the highest scoring intentful sequences after 6 epochs of training. In general, both the set of strongest intentful and non-intentful sequences converge quickly.

| Sequence           | Intenful Rate |
|--------------------|---------------|
| i want to know     | 220.17        |
| that we need to    | 175.59        |
| i must say         | 164.11        |
| and we need to     | 163.44        |
| i will give        | 159.38        |
| i must admit       | 158.03        |
| i ll go            | 141.82        |
| but i want         | 135.07        |
| i ll post          | 125.62        |
| must say that      | 122.91        |
| we don t need to   | 122.91        |
| i ll just          | 118.86        |
| i must say that    | 117.51        |
| i will make        | 109.41        |
| i ll keep          | 108.06        |

Figure 3 shows the convergence of the deep learner for intent. This figure should be interpreted with care because the labels are changing from one epoch to the next, but the convergence is clear.

The effect of each epoch on the label consensus is shown in Figure 4. The set of high-intent segments do change, but not enough to be visible at the top of the figure; the non-intent segments rapidly increase.

Figure 5 shows the convergence of the deep learner for abusive language.

Tables IX, X and XI show the highest ranking segments sorted by predicted intent score, with the corresponding abuse and abusive-intent scores shown as well. Unsurprisingly in these contexts there is considerable correlation between intent and abuse.

Figure 6 shows Shapley values for the individual words in an example, illustrating which words have an impact on the predictions. The abusive language model identifies “kill you”
while the intent model identifies the multiple occurrences of “I will”.

Figure XII shows the segments making up entire documents.

A. Comparison with human judgements

Since the labelling process is inductive, we use agreement with human assessments as a validation technique. A website was created in which volunteers could label segments as intentful or not, and abusive or not. Each volunteer received tranches of 5 segments, plus a qualifying example (not from the dataset and constructed with a known label). Tranches in which a user answered incorrectly to the qualifying question were discarded. No volunteer received more than 30 examples (6 tranches) to label.

The samples shown to volunteers were sampled from the extremes of the labelling, that is segments whose labels were either in [0, 0.4] or [0.6, 1]. A total of 5000 segments were randomly selected and randomly presented to participants. Each segment was scored on a first to 3 basis (that is, 3 consistent votes up to a maximum of 5 total votes) and removed from the candidate set when it had received 3 consistent votes. User predictions were scored as binary (majority intentful or non-intentful) and weighted (the ratio of votes for intentful to total votes).

The agreement with the computational predictive model was 80% on a binary basis, and 81% on a weighted basis (that is, comparing weighted human labelling to real-valued intent labels). This suggests that some examples that the intent predictor found difficult were also ones on which human raters disagreed.

Inter-rater agreement above 70% are normally considered adequate, so these results support that the intent predictor is performing well, especially as intent is a subjective category.
for humans.

Fig. 7: Confusion matrix for intent model using validation labels

The confusion matrix between model and human predictions is shown in Figure 7. Raters found considerably more intent than the predictive model did. Tables XIII and XIV show examples where the model and human raters disagreed. In some cases the human raters considered segments with past tenses as conveying intent (“I decided to join”, “I wanted to feel”). In other cases, they saw what is arguably a weak form of intent (“I may well respond”) which the model does not see. Phrases such as “it going to be splat time” do not contain any linguistic signals of intent but were plausibly considered to be (at least potential) intent.

For the examples where the model detected intent but the human scorers didn’t, it is clear that humans do not consider “we need” or “we want” to be expressing intent. However, “we continue to kick” and “we are going to be labelled” are clearly mistaken intent prediction by the model. These divergences suggest that the model could be improved by paying more attention to first-person plural pronouns, since the human scorers clearly believe that these are weaker signals of intent: “I need to” is regarded as much stronger than “we need to”.

VI. CONCLUSIONS

We address the problem of detecting posts that convey both abusive content and the intent to act, and so are targets for intelligence analysts. We build a predictive system that infers signals of intent from unlabelled data and a small seed set, using both an n-gram and a deep-learning approach, acting as colearners. The merged labels become stable within only a few rounds. We combine this with a deep-learning biLSTM for abusive language, and design ways to score individual segments on intent, abuse, and abusive intent; and score entire documents based on the scores of their segments. We appeal to face validation by showing the highest-scoring segments, and compare the predictions of the model with human scorers, achieving an agreement of 80% for class labels and 81% for regression.

The methodology developed here can be applied to any other linguistic property for which an appropriate seed set and template can be defined.
TABLE X: Examples of a range of segments: Manifesto

| Abuse | Intent | Product | Segment |
|-------|--------|---------|---------|
| 0.968 | 0.999  | 0.967   | we will kill you and drive you reaches from our lands |
| 0.922 | 0.996  | 0.918   | if you are released we will find you and kill you if you are in prison we will reach you there if you try to hide these rapist scum we will kill you as well |
| 0.894 | 0.998  | 0.892   | i will wipe you the fuck out with precision the likes of which has never been seen before on this earth mark my fucking words |
| 0.857 | 0.975  | 0.836   | not only am i extensively trained in unarmed combat but i have access to the entire arsenal of the united states marine corps and i will use it to its full extent to wipe your miserable ass off the face of the continent you little shit |
| 0.751 | 1.000  | 0.751   | we must crush immigration and deport those invaders already living on our soil |
| 0.586 | 0.967  | 0.566   | i will shit fury all over you and you will drown in it |
| 0.314 | 0.993  | 0.312   | in the end we must return to replacement fertility levels or it will kill us |
| 0.285 | 0.980  | 0.280   | i want your neck under my boot |
| 0.272 | 0.994  | 0.270   | thus before we deal with the fertility rates we must deal with both the invaders within our lands and the invaders that seek to enter our lands |
| 0.207 | 0.978  | 0.203   | then i will commit suicide happy in the knowledge i did my best to prevent the death of my race |
| 0.347 | 0.412  | 0.143   | these i hate |
| 0.684 | 0.195  | 0.133   | would you rather do the killing or leave it to your children |
| 0.253 | 0.372  | 0.094   | both illegal and legal drug dealers are our racial enemies ruining the health wealth family structure culture and future of our people |
| 0.237 | 0.228  | 0.079   | i am a racist |
| 0.076 | 0.999  | 0.967   | we must thrive we must march ever forward to our place among the stars and we will reach the destiny our people deserve |

TABLE XI: Examples of segments with high abusive intent: Iron March

| Abuse | Intent | Product | Segment |
|-------|--------|---------|---------|
| 0.965 | 0.993  | 0.958   | a i m not going to clean that shit up and merge your posts every time you fucking do it if you persist i ll suspend you for a week go reinroduce yourself you faggot joined less than posts who the fuck even remembers you at this point |
| 0.953 | 0.998  | 0.951   | he is a fucking retard and i want to organize a massive troll on him |
| 0.910 | 0.999  | 0.909   | if you suicide i ll kill you |
| 0.918 | 0.977  | 0.897   | once i m done here i m going to spam the fuck out of the forums as a final fuck you |
| 0.899 | 0.996  | 0.895   | a i ll end that here because being british sounds snarky as fuck |
| 0.945 | 0.945  | 0.894   | a anyway i love to get the fuck away from this cesspit |
| 0.895 | 0.991  | 0.887   | if they don t i ll fuck them off |
| 0.891 | 0.994  | 0.885   | hahah you re a retard like me then we ll make good company |
| 0.882 | 0.999  | 0.881   | i ll leave you to wonder which i am talking about while i blush like an idiot |
| 0.906 | 0.960  | 0.870   | a also they pretty much know i ll fuck off to the motherland aftera |
| 0.862 | 0.997  | 0.860   | i like to make it clear i m not a fucking dick sucker that s all but that s how young guys are they idolise anyone who is what they don t dare be |
| 0.858 | 0.996  | 0.854   | what the literal fuck sometimes i just want to delete tumblr |
| 0.851 | 0.997  | 0.848   | clean cut but i ll still throw down with niggers |
| 0.873 | 0.967  | 0.844   | maybe i will you lazy faggot |
| 0.841 | 0.996  | 0.838   | a carrying on with being a british cuck i want to leave the eu so i don t see mongol fuckers like you stealing my money |

TABLE XII: Examples of entire documents with abuse and intent scores for each segment. Each group of segments is from one document.

| Abuse | Intent | Product | Segment |
|-------|--------|---------|---------|
| 0.901 | 0.987  | 0.890   | we need to stop being soft hiding behind a wall of tolerance and start kicking some black and muslim ass |
| 0.028 | 0.004  | 0.000   | make them uncomfortable in europe by being more open with our nationalistic pride |
| 0.905 | 0.015  | 0.014   | i cant even make it past one or two of these idiots emma west has more guts than all these idiots |
| 0.028 | 0.981  | 0.028   | to think that she is sitting in jail right now for speaking the truth makes me really mad i want to find her and give her a hug and thank her for being awesome |
| 0.947 | 0.002  | 0.002   | you are all totally stupid |
| 0.000 | 0.959  | 0.000   | i was submitting a satirical post analo- gous to all of those which i continue to read on this website |
| 0.234 | 0.017  | 0.012   | non sensible pretentious etc etc |
| 0.022 | 0.000  | 0.000   | erm read the title of the thread a typical wn thread |
| 0.018 | 0.002  | 0.000   | yes you are all terribly bright peopleloleyes |
| 0.005 | 0.000  | 0.000   | the post was called posticus b s icus |
| 0.923 | 0.001  | 0.001   | sean taylor is a stupid ape |
| 0.001 | 0.960  | 0.001   | that i will remember him that way |

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we can speculate all we want except we just want to be left alone by races

we are going to be labeled hatred eaten com but i want to make sure i dont

we need a virus that attacks jews and make them get off their asses like every one else has to and work for it

we just want to be left alone by races that history has shown can t wipe their own arse without instructions and a tonne of aid money

we need to return to medieval era capital punishments for these violent savage animal mads

we are going to be labeled hatred eaten bigots no matter what we do because there are large well funded jew organizations that watch every move we make

it s seriously starting to grind my nerves and i truly want to know who or what the f is being retarded and bothering me

jaw watch jewish atrocities slave trade jewish slave ship owners quote for decades the white people of america have been subjected to a continual barrage from blacks and others that you and i are somehow responsible for the african slave trade and that we need to atone for our guilt

we need to be in the middle east like we need a second asshole

we can speculate all we want except for the cases of obese self esteem issues women but i m convinced there s something important here we re missing along the lines of why well to do pretty white girls lived abusive lives with charles manson and why hetero women with sexual trauma abuse in their pasts become strippers and porn starts and turn bisexual or lesbian

we need that here but the problem is getting people off their asses

we need a virus that attacks jews and non whites

com but i want to make sure i dont sound like a dumbass

more like future racist car thief murderer racist murderer either way prison or welfare we will support them
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