Predicting Opinion Leaders in Word-of-Mouth Communities

Gelareh Towhidi
Lubar School of Business
University of Wisconsin-Milwaukee
gtowhidi@uwm.edu

Atish P. Sinha
Lubar School of Business
University of Wisconsin-Milwaukee
sinha@uwm.edu

Abstract
Opinion leaders play a major role in shaping potential customers’ minds in word-of-mouth communities. Prior research on opinion leaders in word-of-mouth communities has focused mostly on structural characteristics of social networks of the leaders, ignoring the predictive potential of the actual text that they write. We argue that textual characteristics of reviews, along with reviewer characteristics, could be used to predict opinion leadership. In this paper, we propose a predictive model to identify opinion leaders in online word-of-mouth communities using both review and reviewer characteristics. The results from our study indicate that the predictive performance of the classification models built using the proposed predictors is much better than that of a baseline bag-of-words model built using the actual review text.

Keywords
Opinion leader, word-of-mouth communities, online reviews, predictive model, text mining.

Introduction
Opinion leaders play a prominent role in shaping potential customers’ minds in word-of-mouth (WOM) communities. Previous studies on opinion leaders in WOM communities have mostly focused on social network characteristics of the leaders, ignoring the predictive potential of the actual text that they write (Ku et al. 2012; Li and Du 2011; Lu et al. 2012). Textual characteristics of reviews such as readability, comprehensiveness, and objectiveness, as well as embedded emotion and sentiment of reviews, have been used to predict review helpfulness and product sales (Ghose and Ipeirotis 2011; Hu et al. 2008; Liu et al. 2007; Otterbacher 2009; Schindler and Bickart 2012; Yin et al. 2014). Similarly, reviewer characteristics such as reviewer disclosure, reviewer history, and reviewer reputation have been considered as important factors influencing review helpfulness and product sales (Ghose and Ipeirotis 2011; Li et al. 2013a; O’Mahony and Smyth 2010; Otterbacher 2009). In WOM communities, textual characteristics of reviews have been used before for predicting review helpfulness and sales, but not for classifying reviewers as opinion leaders. We argue that textual characteristics of reviews, along with reviewer characteristics, could be used to predict opinion leadership.

In this paper, we propose a predictive model for identifying opinion leaders in online WOM communities using textual (review) and reviewer characteristics. In prior research, the structural features of nodes in a friendship, blog, or trust network have been used to predict prestigious members of communities (Ku et al. 2012; Li and Du 2011; Li et al. 2013b; Lin et al. 2013; Lu et al. 2012; Ma and Liu 2014). Our predictive model could be generalized to any word-of-mouth community without a friendship or trust network. We empirically examine the predictive power of our model using a review dataset from Amazon.com. Using the review and reviewer characteristics, we build classification models for opinion leadership in WOM communities. The results from our study indicate that the predictive performance of the classification models built using the proposed predictors is much superior to that of a baseline bag-of-words model built using the actual review text.
Literature Review

Product reviews provide a reliable source of information of customer's opinions and preferences on products. Online product reviews could affect customers' purchase intention and product sales (Jiménez and Mendoza 2013; Mudambi and Schuff 2010; Trusov et al. 2009; Wei and Lu 2013). However, the large number of online product reviews, some of which could be very long and unclear, makes it difficult to understand the customers' true opinions and concerns. Furthermore, multiple sources of reviews make the task of analyzing and extracting useful information more difficult.

Because of the difficulties discussed above, the topic of online review helpfulness has received quite a lot of attention during the last few years. Most of those studies have evaluated the textual characteristics of online reviews to develop review helpfulness models. Cao et al. (2011) investigated the effect of different textual characteristics of the reviews on helpfulness by applying the text mining approach. These characteristics include basic (pros and cons, summary, posting date, extremeness level), stylistic (number of words, number of sentences, number of words in title, pros and cons, summary), and semantic characteristics of reviews. Their results showed that all these factors together have a significant effect on the helpfulness votes that a review receives.

Otterbacher (2009) identified five factors of online review helpfulness: relevancy, reputation, representation, believability, and objectivity. Hoang et al. (2008) used a classification approach to examine the quality of user-created documents based on authority, formality, readability, and subjectivity. O’Mahony and Smyth (2010) developed a recommendation system to identify the most helpful reviews by applying a supervised classification approach. They used reviewer characteristics such as reputation, social, and sentiment features, in addition to review textual features. Ghose and Ipeirotis (2011) examined the influence of the textual features of reviews such as informativeness, subjectivity, and readability, in addition to reviewer-level features such as average usefulness of past reviews and self-disclosed identity, on product sales and perceived usefulness.

The study by Schindler and Bickart (2012) suggests that a review's length, stylistic elements, sentiment, and information affect the perceived helpfulness of an online product review. Li et al. (2013a) argued that source and content-based review features have direct a direct impact on product review helpfulness. The factors that they identified as influencing review helpfulness include perceived source credibility, perceived content diagnosticity, and perceived vicarious expression of the review. In another related study, Yin et al. (2014) examined the effects of emotions embedded in product reviews on perceived helpfulness by readers. They investigated the roles of two negative emotions common to reviews: anxiety and anger. Their empirical results showed the importance of examining the emotions in online word-of-mouth comments and the differential impacts of anxiety and anger on perceived reviewer effort.

All the studies mentioned above focus on predicting review helpfulness or product sales using textual features of the reviews. But none of those studies addressed the issue of opinion leadership. In this paper, we argue that the textual features of online reviews could also be applied to identify opinion leaders in online WOM communities.

In the context of social networks, some studies have developed the theoretical foundations for analyzing the role and effect of opinion leaders (Freeman 1979; Venkatraman 1989). Wasserman (1994) discussed concepts such as network structures and relations, centrality and prestige, structural balance and transitivity, social groups and subgroups, and roles and positions in social networks. Author reputation, which includes expertise and centrality, has been considered to be an important factor in influencing others’ attitudes toward opinion leaders. Similarly, knowledge, experience, innovation, and communication are important factors for author popularity in online social networks (Bansal and Voyer 2000; Mitchell and Dacin 1996).

Brown et al. (2007) found that the credibility of information (expertise and bias) is an important factor for readers in evaluating the value of that information in online WOM communications. Source expertise is related to information source competence, and source bias is information source trustworthiness. Therefore, a credible source has more expertise and less bias. Kaiser and Bodendorf (2009) presented an approach considering communication and relationships among customers, as well as the content of the conversations. They used a four-step approach for detecting opinion evolvement and identifying opinion leaders; the steps are: extracting users’ opinion, identifying communication relationship among users,
forming a graph of the social networks of users, their opinions and their communication, and then analyzing key figures of the graph to find opinion leaders and trends.

In a related study, Lu et al. (2012) relied on network theory and used the same indicators for “centrality” proposed by Kaiser and Bodendorf (2009) – degree centrality, closeness centrality, and betweenness centrality – to quantify members’ prestige in a social network. They focused on predicting the emergence of prestigious members in the near future by using a sequence of snapshots of a network over a given time horizon. Ku et al. (2012) identified reputable members in online opinion-sharing communities using network features. Their research indicates that the influential factors are: trust intensity of the member, degree of review focus in the target category, and the average product rating given by the member. Similarly, using network features, Lin et al. (2013) investigated the characteristics of opinion leaders in the Microblog network. They found that authority of the participating individuals is the most important factor of opinion leaders. They examined opinion leaders’ characteristics using an AHP model based on the influence, support, and activity of a node, and microblog-rank algorithm based on the weighted undirected network. Ma and Liu (2014) also proposed the SuperedgeRank algorithm for opinion leader identification based on supernetwork theory, combining the network topology features and text mining. Li et al. (2013b) proposed a framework for opinion leader identification using blogger networks’ content and communications. They identified expertise, novelty, influence, and activity as four distinguishing features for opinion leaders. They also investigated longevity and centrality of opinion leaders in blogging networks.

The studies discussed above focused on the structural features of online social networks that offer friendship, or those of trust networks such as Blogosphere, Epinion.com, etc. However, some WOM communities (e.g., Amazon.com) do not offer friendship or trust relationship networks. Not having the structural features of the social network makes it difficult to predict who would be the most influential member in an online WOM community. Therefore, we examine a set of features for predicting opinion leaders; these features can be applied in any type of WOM community, even in those without a trust network. Also, we believe that structural features are not sufficient for predicting opinion leadership. We therefore propose a model which includes both textual features of reviews and reviewer characteristics to predict opinion leadership.

**Predictive Model of Opinion Leadership**

Online product reviews have become one of the most important information sources for purchase decision making and for new product/service promotion and diffusion. Opinion leaders are those members of word-of-mouth communities who improve information exchange, public opinion formation, and communication in the community. They are prestigious members with higher status who influence attitudes, opinions, actions, and communication of other members, as well as facilitate community connection. They are also important for online retailers such as Amazon.com to gain critical consumer insights into their products and services.

Opinion leaders could provide useful information, such as potential problems of products, services and deliveries, competitive advantages of current products and services, potential market segments, and future demands of consumers. Otterbacher (2009) found that a reviewer’s rank in community (which is based on the total number of reviews and the total number of helpful votes) is a measure of reviewer reputation. Furthermore, member’s reputation or rank has been conceived as opinion leadership status in previous studies (Ku et al. 2012; Lin et al. 2013; Ma and Liu 2014). Amazon.com ranks customer reviewers based on other customers’ votes on helpfulness of reviews. A reviewer’s rank is determined “by the overall helpfulness of all their reviews, factoring in the number of reviews they have written” (Amazon.com). In addition to review helpfulness, reviewer rank helps consumers to find more credible reviews among thousands of reviews for a specific product. Reviews written by reviewers who have been awarded the “top reviewer badge” in Amazon.com are more credible and influential. Following previous studies, we consider reviewer rank to be a measure for opinion leadership.

We believe that opinion leaders have some specific behavioral and contextual characteristics in common, such as being more active, knowledgeable, trustworthy, and objective. We define our predictive model of opinion leadership in word-of-communities by focusing on reviewer characteristics and review textual
characteristics. Based on these features, we build and evaluate classification models for predicting opinion leadership. We describe below the review and reviewer features that we use as predictors.

**Review Features**

**Activity Generation** is considered as the post capability of generating activities in the community. The number of comments the review has received is a measure of the amount of discussion it has generated in the community (Agarwal et al. 2008). Because opinion leaders create and encourage activity in the community, a review with more comments indicates that the reviewer has a higher likelihood of being an opinion leader.

**Extremeness** is the extent to which the review product rating is different from the average of all user ratings (Cao et al. 2011; Chen and Tseng 2011). It measures how surprising the review is compared to all the other reviewers.

**Relevancy** is the extent to which the review helps to make a decision and provide a large amount of product information (Chen and Tseng 2011). It is also considered as the extent to which it contains important words across reviews (Otterbacher 2009). Because relevant reviews are informative and credible, we expect a reviewer who writes a more relevant review to be more likely to be an opinion leader.

**Objectivity** is the extent to which the review is textualy similar to the product description, and subjectivity indicates how different the review is from that description. Subjective opinions in reviews are likely to help readers make decisions (Chen and Tseng 2011; Ghose and Ipeirotis 2011; Liu et al. 2007).

**Rating Polarity** is the product rating assigned by a review.

**Readability** is the extent to which readers expend effort in reading the reviews. A readable review should state clear and direct opinions, and not contain spelling mistakes (Chen and Tseng 2011; Ghose and Ipeirotis 2011). Some studies also considered the lexical density and the length of the review as important factors for review readability (Hoang et al. 2008; Liu et al. 2007).

**Sentiment** is considered to be the overall polarity of the review text. The sentiment of a review is the overall polarity of the reviewer’s opinion about the product, extracted by mining the actual text of the reviews. It has been argued that high polarity agreements are expected between opinion leaders and their followers, since opinion leaders try to convince their followers to have the same opinion toward a specific product (Kaiser and Bodendorf 2009).

**Timeliness** is the extent to which the review is timely and up-to-date (Chen and Tseng 2011; Otterbacher 2009). We expect a reviewer who posts his/her review in a timely manner – i.e., as quickly as possible after the first review of the product is posted – to have a higher chance of being an opinion leader.

**Reviewer Characteristics**

**Authority** is measured by the number of reviews previously written by the reviewer (Chen and Tseng 2011; Hoang et al. 2008; Otterbacher 2009). Reviews written by authoritative reviewers tend to be more influential (Chen and Tseng 2011).

**Credibility** is the extent to which the information source is believable (Hovland et al. 1953). Credibility is viewed as a perceived quality of information and is evaluated simultaneously with two components: trustworthiness and expertise (Rubin and Liddy 2006). Expertise is considered to be the perceived knowledge or competence of the author and is described with terms such as knowledgeable, reputable, and competent (Brown et al. 2007; Rubin and Liddy 2006; Tseng and Fogg 1999). Trustworthiness is considered to be the goodness or morality of the author and is described with terms such as well-intentioned, truthful, or unbiased (Brown et al. 2007; Rubin and Liddy 2006; Tseng and Fogg 1999). A reviewer who is perceived as more credible by other community members is more likely to be an opinion leader.

**Disclosure** is considered to be the social information about reviewers in the community. This kind of information is likely to be an important factor affecting readers’ decisions (Forman et al. 2008; Ghose and Ipeirotis 2011).
Recency is the extent to which a reviewer has been recently active in the community (Ngo-Ye and Sinha 2014).

Data Collection

Amazon.com provides online reviews for products and services by using “community-based voting techniques” called “social navigation” (Gilbert and Karahalios 2010; Ngo-Ye and Sinha 2014). Customers can express their opinions, sort reviews by different preferences, rate the helpfulness of the reviews, and write comments on the reviews. For the purpose of this study, a sample of 1200 reviews, including all the reviews for iPhone5 and iPad3 posted on or before May 2013, was collected. Furthermore, all other available information on the review, such as star rating, helpfulness votes, number of comments, in addition to the reviewers’ profile information, was collected. We only considered the reviews posted by February 2013 to make sure that they had sufficient exposure to be voted by readers. To get a more balanced dataset, we considered those reviewers ranked in the top 500,000 as opinion leaders and those in the bottom 5,000,000 as not. The data set we finally used for building the classification models contains 561 reviews, out of which 215 are opinion leaders.

Measures

Activity generation: the number of comments of others on the review.

Extremeness: the absolute value of the difference between the reviewer’s rating of the product and the average of all user ratings.

Objectivity: the percentage of objective sentences in the review (we used the OpinionFinder2.0 Natural Language Processing tool to calculate review objectivity).

Rating polarity: for each review, we considered a 4 or 5 star rating as positive polarity, a 3 star rating as neutral, and 1 or 2 as negative polarity.

Readability: Fog index, which indicates the number of years of formal education a reader of average intelligence would need to understand the text on the first reading (we used the Fathom package in Java to calculate Fog index).

Relevancy: the relevancy of each review to the related product under review (iPhone5 or iPad3). We used the AlchemyAPI Natural Language Processing tool to measure relevancy. The concept tagging API is capable of understanding how concepts relate, and can identify concepts that are not necessarily directly referenced in the text. A relevance score is calculated for each concept based on statistical analysis, and the results are returned, sorted by relevancy. We used the relevance score based on the keyword “iPhone” for the reviews of iPhone5, and the relevance score based on the keyword “iPad” for the reviews of iPad3.

Sentiment: the overall polarity of the review text. We used the sentiment analysis API of AlchemyAPI to determine review sentiment. AlchemyAPI's sentiment analysis algorithm looks for words that carry a positive or negative sentiment and then finds to which person, place, or thing they are referring to. It also understands negations (i.e., "this car is good" vs. "this car is not good") and modifiers (i.e. "this car is good" vs. "this car is really good"). We used the sentiment calculated for the overall review to determine if it is positive, negative, or neutral.

Timeliness: the interval (number of days) between the current review and the first review of the product.

Authority: the number of reviews previously written by the reviewer.

Credibility: the extent to which the information source is believable. Since credibility is a perception construct, a survey was administered to students in a business school to measure their perceptions of reviewer credibility, in terms of expertise and trustworthiness, for each review. Based on the theoretical background presented earlier, we presented a set of reviews to the students and asked them to rate each reviewer on the following four items: In-depth knowledge, Comprehensive knowledge, Competence, and Accuracy. Next, we calculated the average of all of the four items to get the reviewer expertise score. Similarly, for trustworthiness, we asked the students to rate each reviewer on the following four items: Honesty, Fairness, Believability, and Not making a sales pitch. Next, we calculated the average of all of the
four items to get the reviewer trustworthiness score. Finally, Principal Component Analysis was performed to derive the credibility factor.

Disclosure: any disclosure of social information about the reviewer. If the reviewer discloses any of the following information, then his/her disclosure score would be “yes”, otherwise “no”: real name, real photo, email, and website.

Recency: the number of days between the last postdate and the postdate of the current review.

The measures discussed above are summarized in Table 1.

<table>
<thead>
<tr>
<th>Measures</th>
<th>Description</th>
<th>Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>Activity Generation (log)</td>
<td>Number of comments of others on the review</td>
<td>Numeric</td>
</tr>
<tr>
<td>Extremeness</td>
<td>Absolute value of the difference between the reviewer’s product rating and the average of all user ratings</td>
<td>Numeric</td>
</tr>
<tr>
<td>Relevancy</td>
<td>Relevance of the review to the product under review</td>
<td>Numeric</td>
</tr>
<tr>
<td>Objectivity (log)</td>
<td>Percentage of objective sentences (similar to the product description) in the review</td>
<td>Numeric</td>
</tr>
<tr>
<td>Rating Polarity</td>
<td>Overall polarity of the product rating</td>
<td>Categorical (positive, neutral, negative)</td>
</tr>
<tr>
<td>Readability</td>
<td>Fog index (the number of years of formal education a reader of average intelligence would need to understand the text on the first reading)</td>
<td>Numeric</td>
</tr>
<tr>
<td>Text Sentiment</td>
<td>Overall polarity of the review text</td>
<td>Categorical (positive, neutral, negative)</td>
</tr>
<tr>
<td>Timeliness (log)</td>
<td>Number of days between the current review and the first review of the product</td>
<td>Numeric</td>
</tr>
<tr>
<td>Authority (log)</td>
<td>Number of reviews previously written by the reviewer</td>
<td>Numeric</td>
</tr>
<tr>
<td>Credibility</td>
<td>Extent to which the reviewer is perceived to be credible, in terms of expertise and trustworthiness</td>
<td>Numeric</td>
</tr>
<tr>
<td>Disclosure</td>
<td>Whether reviewer discloses his/her real name, real photo, email, or website</td>
<td>Categorical (yes/no)</td>
</tr>
<tr>
<td>Recency (log)</td>
<td>Number of days between the last postdate and the postdate of the current review</td>
<td>Numeric</td>
</tr>
<tr>
<td>Opinion Leader (dependent variable)</td>
<td>Whether reviewer is ranked in the top 500,000</td>
<td>Categorical (yes/no)</td>
</tr>
</tbody>
</table>

**Table 1. Measures used in predictive model for opinion leadership**
Results

Using all the measures for opinion leadership (see Table 1), we built our predictive model. We used Weka 3.6.9 to build the classification models, and then applied 10-fold cross-validation to evaluate the performance of the models. We used J48 decision tree, logistic regression, neural network, random forest, and support vector machine as classifiers.

The baseline model is the bag-of-words model. We applied the standard preprocessing steps to prepare the sample corpus for the bag-of-words model. We used the snowball stemmer, stopword eliminator, and word tokenizer methods. More specifically, English stop words were filtered, the text strings were tokenized using a set of delimiters, all terms were changed to lower case and stemmed to their common roots, and finally the input terms for the classification model were identified. To build the bag-of-words model, a CSF subset evaluator with best-first search method was used on the training data set to select a subset of words that would be used for classifying opinion leaders. Among all the bag-of-words classifiers, the support vector machine produced the best performance results (using 10-fold cross-validation); these results are reported below for the baseline model.

The results for all the predictive models are summarized in Table 2. We evaluated the predictive models according to the following criteria: accuracy, true positive rate, false positive rate, precision, recall, F-measure, and ROC Area. The results show that all the classifiers built using our proposed predictors perform much better than the baseline text mining model. Among them, the Support Vector Machine performs the best with respect to all measures (accuracy = 85.03%, precision = 0.854, recall = 0.850, F-measure = 0.851), except for ROC area (0.849), which is lower than that of logistic regression, random forest, and neural network. Its performance is much better than that of the baseline bag-of-words model (accuracy=77.01%, precision = 0.767, recall = 0.770, F-measure=0.766, ROC area = 0.742), which was built using the actual text of the reviews.

<table>
<thead>
<tr>
<th>Model</th>
<th>Correctly Classified</th>
<th>TP Rate</th>
<th>FP Rate</th>
<th>Precision</th>
<th>Recall</th>
<th>F-Measure</th>
<th>ROC Area</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>77.01</td>
<td>0.770</td>
<td>0.285</td>
<td>0.767</td>
<td>0.770</td>
<td>0.766</td>
<td>0.742</td>
</tr>
<tr>
<td>J48</td>
<td>81.64</td>
<td>0.816</td>
<td>0.208</td>
<td>0.816</td>
<td>0.816</td>
<td>0.816</td>
<td>0.798</td>
</tr>
<tr>
<td>LR</td>
<td>82.71</td>
<td>0.827</td>
<td>0.194</td>
<td>0.827</td>
<td>0.827</td>
<td>0.827</td>
<td>0.920</td>
</tr>
<tr>
<td>NN</td>
<td>82.35</td>
<td>0.824</td>
<td>0.202</td>
<td>0.823</td>
<td>0.824</td>
<td>0.823</td>
<td>0.899</td>
</tr>
<tr>
<td>RF</td>
<td>83.60</td>
<td>0.836</td>
<td>0.162</td>
<td>0.842</td>
<td>0.836</td>
<td>0.837</td>
<td>0.919</td>
</tr>
<tr>
<td>SVM</td>
<td>85.03</td>
<td>0.850</td>
<td>0.151</td>
<td>0.854</td>
<td>0.850</td>
<td>0.851</td>
<td>0.849</td>
</tr>
</tbody>
</table>

| Baseline: bag-of-words model; | J48: decision tree; | LR: logistic regression; | NN: neural network; | RF: random forest; | SVM: support vector machine |

Table 2. Performance of predictive models

Conclusion and Future Directions

In this paper, we developed and evaluated a set of predictive models that identify opinion leaders in online word-of-mouth communities using two sets of characteristics, one for the review and the other for the reviewer. The results show that predictive models built using the proposed review and reviewer characteristics perform significantly better than the baseline model, which is a bag-of-words model based on the actual review text. Based on the results, we can conclude that the textual characteristics of reviews written by a reviewer, along with a set of reviewer features, are important for determining if he or she is an opinion leader in a WOM community.

This study contributes to the past research by examining new factors for identifying opinion leaders in online WOM communities. First, textual characteristics of reviews have been used before for predicting review helpfulness and sales, but not for opinion leadership. In this study, we showed that textual
characteristics of the reviews, along with reviewer characteristics, are also effective predictors of opinion leadership status. Second, we showed that extracting textual features as predictors, and using them in conjunction with reviewer features, results in better prediction of opinion leadership than using the actual text of reviews.

Third, in past research, structural features of nodes in a friendship or trust network have been used to predict prestigious members of communities. However, not every online WOM community offers a friendship or trust network. In this study, we investigated the predictive power of reviewer characteristics on opinion leadership in a way that could be generalized to any online WOM community. Fourth, we introduced new predictors for identifying opinion leaders such as credibility and disclosure, which have not been used before in this context.

Fifth, this study is the first attempt at introducing a comprehensive model which brings together review textual characteristics and reviewer characteristics for classifying opinion leaders among online reviewers. The classification models built using the proposed predictors exhibit significant improvement in performance over the baseline bag-of-words model. Finally, our study has practical implications for online retailers like Amazon.com. Opinion leaders are of great importance to such retailers because they provide useful information such as potential problems of products and deliveries, competitive advantages of current products, potential new market segments, and future market demands. Our model enables online retailers to predict opinion leaders whose reviews are helpful for gaining critical consumer insights into products and services.

One limitation of our study is that the credibility measure used in the study was based on the evaluation of one review by a student. In the future, a more reliable estimate of credibility could be derived by asking human evaluators to rate a sample of reviews written by the reviewer. Another limitation is that we tested our predictive models on only two products in the field of electronics (iPhone and iPad), based on reviews available on Amazon.com. In the future, we plan to investigate the performance of our models for different product categories. That would help us generalize the results across different product categories. Furthermore, we plan to investigate the performance of our models for different social communities such as trust or friendship communities. We plan to investigate if the interplay between the review/reviewer characteristics we have used in this study and other network features such as homophily and tie strength have any impact on opinion leadership in those communities.
REFERENCES


